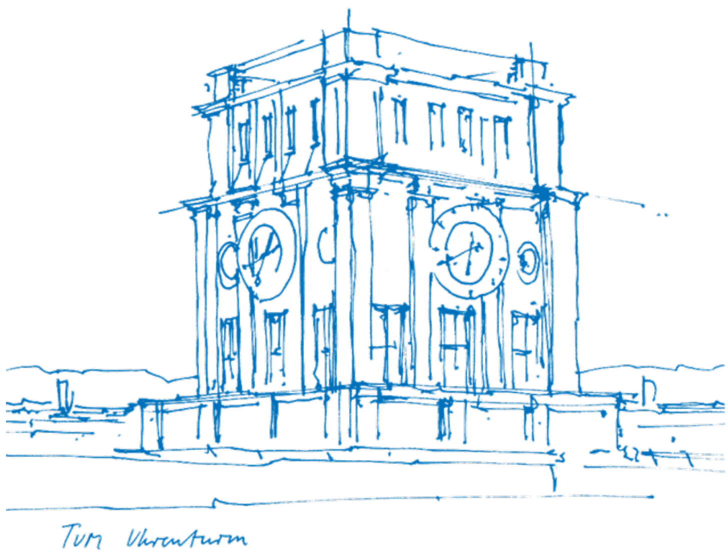
Chair of Urban Structure and Transport Planning
TUM School of Engineering and Design
Technical University of Munich

Who is affected more by the lack of transit network resilience?

Local and regional level social analysis for resilient public transportation system

Lena Chan



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Thesis for the attainment of the academic degree

Master of Science (M.Sc.)

at the TUM School of Engineering and Design of the Technical University of Munich.

Examiner:

Dr.-Ing. Benjamin Büttner

Supervisor:

Dr.-Ing. David Duran

Submitted:

Munich, 08.03.2024

I hereby declare that this thesis is entirely the result of my own work except where otherwise indicated. I have only used the resources given in the list of references.

Munich, 08.03.2024 Lena Chan

Professur für Siedlungsstruktur und Verkehrsplanung
Ingenieurfakultät Bau Geo Umwelt
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MASTER'S THESIS

Studiengang M.Sc. Transportation Systems

für Lena Chan
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Title: Who is affected by the lack of transit network resilience?

Background:

As demand for mobility continues to rise, public transport networks must be robust enough to ensure that their services can meet the demand. Public transport networks, especially rail-bound transit systems, are ultimately bounded by infrastructural constraints which limit the extent the network could increase its supply. Therefore, a certain extent of resilience must be added to the network to minimize the risk that areas may be cut off from the network during disruptions such as unpredictable incidents or planned construction work. A direct consequence of lacking resilience in the transit network is deteriorating accessibility both with respect to users and points of interest. In turn, the reduced service supply could not meet the already excessive demand, while other points of interest could only be reached with extended travel times. Incorporating resilience such as providing viable alternative transport options is vital to reduce the effect on passengers during disruptions, especially captive riders who rely on public transport. Hence, lacking resilience and transit accessibility in general affect captive riders more than private cars' users.

As public transit forms a city's mobility backbone, it is vital to identify who is part of the more disadvantaged demographic that potentially cannot access the public transport network. Most of the population cannot afford private cars and thus, an accessible and reliable public transportation system is vital to satisfy their mobility needs. Moreover, disadvantage population, usually, tend to have less access to private cars and to be segregated in the edges of the cities. While there are already location and demographic-specific factors that account for their low accessibility during service without disruption, a low-resiliency network that provides very few to no usable alternatives could drastically drop the already low accessibility, leaving such users stranded in nowhere.

In the case of Munich, Germany, the inner city is covered thoroughly by a multi-modal transit network and a strong hierarchy still exists in the wider Munich Metropolitan Area. Buses in outskirts are mainly feeders to rapid transit, and parallel services are a rarity. This demonstrates a low network resiliency in the suburbs of MMA when compared to other cities.

Despite abundant research available in the fields of network resilience and accessibility on their own, little attention has been given to the intersectionality between these two issues. Particularly, research on the correlation between fairness and network resilience is still in its infancy. Disadvantaged populations are often distributed towards less accessible areas, which are more prone to deteriorating accessibilities during transit disruptions. Despite this, the question of who are more or less affected by a less resilient transit network.

<u>Objectives:</u>

To address the research gap of the above-mentioned intersectionality, the objective of this thesis will be two-fold: (1) to identify the key indicators to measure the correlation between fairness and network resilience, and (2) by using these indicators, to search for the potential demographics and districts in Munich where passengers are more likely to be affected by the lack of network resilience. Future transit projects such as the second trunk line and the new metro lines will also be considered.

<u>Methodology:</u>

To achieve these objectives, the following methods are applied in this thesis:

- Literature review on equitable/fair transit accessibility, transit network resilience, and their measurement methods.
- Accessibility analysis using GIS and GTFS data in Munich (MVV area) to recreate previous and/or hypothetical disruption scenarios and their corresponding replacement service concepts.
- Analysis on such scenarios on how they affect different areas and population groups.

<u>Supervision</u>:

The candidate will present to supervisor Dr.-Ing. David Duran a draft of the structure for the master thesis and a work plan two weeks after this approval. Other supervision meetings will be planned with the candidate when necessary. The Chair of Urban Structure and Transport Planning supports the candidate with the contact to relevant actors and or experts if needed. After two weeks of the submission of the thesis, the candidate must defend it by means of a presentation (20 minutes) and the following discussion. The results are the responsibility of the author. The Chair does not take responsibility for those results.

Dr.-Ing. Benjamin Büttner

Dr.-Ing. David Duran

Abstract

As the mobility backbone of cities, public transport networks must be robust and resilient enough to minimize the risk that area may be cut off from the network during disruptions. Most of the population, especially disadvantaged population groups, rely on public transit, which means equity is one of the important indicators to measure transit system performance. Therefore, this thesis addresses the existing research gap in the intersectionality between accessibility, resilience, and disadvantaged population by developing a methodology to evaluate the decay in accessibility by public transit, and its impact on underprivileged, transit-dependent population segments. To address the lack of objective indicators which could measure the correlation between transit equity and network resilience, and to answer the research question on which population segments are more likely to be affected by the lack of network resilience, measurement indicators were developed to assess distributional impacts of accessibility decay, and the extent of such impacts on transit-dependent population. An accessibility ratio was used to measure the extent accessibility was affected during disruptions to a municipality, and this ratio could be weighted by population compositions to compare the extent of impacts to the population segments considered. A linear regression model was then generated as an extension to determine population groups who are more vulnerable to disruptions. Through a case study in the suburban area of Munich, Germany, using General Transit Feed Specification (GTFS) data from line closures caused by construction, it was found that unemployed and disabled residents were more vulnerable to disruptions in the region. The method could be used with readily available data using common planning methods such as geographical information system (GIS) and the R5 algorithm, making it a versatile tool to support strategic decision-making to achieve equitable public transit systems.

Acknowledgements

First and foremost, I would like to thank my supervisor, Dr. David Duran, for his effort in supervising my thesis. As an expert in accessibility and equity, his expertise has guided me through the most challenging times throughout my master's studies, and I believe he could have been my mentor. His passion into mobility justice also motivated me to comprehend the importance of social equity in transportation systems besides topological and spatial accessibility analyses. Despite his tight schedules and occasional business trips, he still managed to undergo periodic meetings with me to follow up my progress and exchange ideas. One side note, this is the first time that I used LaTeXin academic writing, and thank you David for introducing it and teaching me how to get used to this system.

I am also thankful to Aaron Nichols, one of my teachers at the Chair of Urban Structure and Transport Planning. His tutorials on accessibility modeling were really useful, not just in my projects and thesis, but the methods I have learned could be applied in my future career to improve transit networks by identifying deficiencies in accessibility. I especially appreciate his efforts as I troubleshoot through using QGIS and R5R throughout the previous modules and my thesis. Learning new software is often exciting but also challenging, and I am grateful to have such a nice tutor to guide me through my learning process.

Thirdly, acknowledgements are given to the Prof. Rolf Moeckel and his colleagues in the Associate Professorship of Travel Behavior for their continuing research on travel demand models, and the permission for using their 2011 Munich synthetic travel demand. This synthetic travel demand represents an important part of accessibility research as I could know which links are more often traveled and thus more vulnerable to disruptions. I appreciate the team's efforts on this and would look forward to more detailed models that incorporate the traveler's individual characteristics, so that we can have a more detailed view of the demographics and model more accurately.

Moreover, I would like to thank Martin Margreiter from the Chair of Traffic Engineering and Control for being my mentor through the TUM Mentoring program. We often exchanged experiences and ideas during regular meetings, and he also guided me on how I could propose a thesis topic, and how I can proceed into the job market after graduation. Without him, my life would have been much harder when I have nobody to talk to and I would had to deal with everything alone.

Lastly, I am extending my gratitude to my parents, Stanley and Winnie, far back in Hong Kong, for their unconditional support. I have been interested in public transport since my childhood, and I am grateful that they supported me to explore this specialized interest for years and integrate this into my studies. In the times when transport enthusiasts are being negatively labeled and attacked around the world, I have reflected how important parental support could be, and thank you for letting me becoming who I want to be.

Contents

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List of Abbreviations

GIS geographical information system. xi, 13, 47, 48

GTFS General Transit Feed Specification. xi, xxi, 13, 28, 41, 44

GTFS-RT GTFS Realtime. 44, 47, 48

LRT light rail transit. 5

MiD Mobilität in Deutschland. 21, 28

MVV Munich Transport and Tariff Association. 19, 27, 43, 48

O-D origin-destination. 8–10, 13, 15, 28, 31, 42, 44

OSM OpenStreetMap. 13, 48

R5 Rapid Realistic Routing on Real-world and Reimagined networks. xi, 15, 41, 44

RAPTOR Round-Based Public Transit Optimized Router. 44, 45

TOD transit-oriented development. 6, 8

VIF variance influence factor. xix, 38, 44

1 Introduction

1.1 Background

As demand for mobility continues to rise, public transport networks must be robust enough to ensure their services can meet the demand. Public transport networks, especially rail-bound transit systems, are ultimately bounded by infrastructural constraints which limit the extent the network could increase its supply. Therefore, a certain extent of resilience must be added to the network to minimize the risk that areas may be cut off from the network during disruptions such as unpredictable incidents or planned construction work. A direct consequence of lacking resilience in the transit network is the loss of connectivity within the network (Derrible & Kennedy, 2009) and thus causes accessibility to deteriorate both with respect to users and opportunities. Research like Geurs and van Wee (2004), Hansen (1959), and Ingram (1971) has established that with lengthened travel times, users could access less destinations during disruptions, while destinations would see smaller catchment areas within the same travel time budget. In turn, the reduced service supply could not meet the already excessive demand, while opportunities could only be reached with extended travel times or extra travel costs. Incorporating resilience such as providing viable alternative options (Xu et al., 2015) is vital to reduce the effect on passengers during disruptions, especially captive riders who rely on public transport. Hence, lacking resilience and transit accessibility in general affect captive riders more than users with access to private cars.

As public transit forms a city's mobility backbone, it is vital to identify who is part of the more disadvantaged demographic that potentially cannot access the public transport network, especially during disruptions which could result in the network being fragmented. Most of the population cannot afford private cars and thus, an accessible and reliable public transportation system is vital to satisfy their mobility needs. The transport planning paradigm however, has been criticized by literature such as Keeling (2008) for the failure to consider social equity aspects, while conflicting goals of maximizing efficiency and prioritizing transit-reliant population have to be met (Delbosc & Currie, 2011; Litman, 2002). Moreover, poor transit service could impair citizens from partaking in social functions, which cause them to be socially excluded (Burchardt et al., 1999; Kenyon et al., 2002). While there are already location, network, and demographic-specific factors that account for the low accessibility during normal service, in case of disruptions, a low-resilience network that provides very few to no usable alternatives could drastically drop the already low accessibility, thus leaving such users spatially and socially excluded.

Radial networks, like the one in Munich, Germany, are especially criticized by the literature such as Laporte et al. (1997) and Saidi et al. (2016) for their low resilience through poor connectivity. These networks mostly have a monocentric layout with lines radiating out from the city center. Whereas the city center might have dense transfer opportunities, regardless of modes, it is very common to have limited to no reliable connections between radial corridors outside the city center, which cause these networks to be poorly connected. This results in circuitous trips and inefficient networks, both contributing to low resilience (Derrible & Kennedy, 2009).

This thesis will study the suburban area of Munich to examine how the lack of resilience in its transit network would impact disadvantaged population. Whereas within the inner city of Munich is covered thoroughly by a multi-modal transit network, a strong hierarchy still exists in the wider Munich Metropolitan Region, where buses in outskirts are mainly feeders to rapid transit, and parallel services are a rarity. This demonstrates a low network resiliency in the region when compared to other cities.

1.2 Objectives of this thesis

Whereas the above topics are extensively studied on their own contexts, little attention was given to the intersectionality between them, namely how resilience could contribute to an equitable public transport network. Studies on equity due to circuity such as Dixit et al. (2021) and Karaaslan and Mert Cubukcu (2023) do not take disruptions or resilience into account, while existing redundancy or resilience studies mostly employ a network-centric approach to create evaluation frameworks rather than assessing demographics or areas that are more vulnerable to disruptions. Moreover, despite studies on impacts of population displacement and gentrification due to transit service improvements, which see less affluent residents losing accessibility either due to increasing costs or residential displacement, and that network fringes are more vulnerable to disruptions, the interactions between such topics remain a niche topic. As less accessible areas often rely on a handful of services as their lifelines to the inner city, it is important to consider the impact caused to these areas should disruption occurs, and by extension, which part of the population would be more severely affected. This thesis therefore aims to address the deficiency in research regarding how transit network resilience could affect users of diverse demographics.

As a result, this thesis will answer the following research questions as an attempt to fill the above research gap:

1. What are the objective indicators that measure the correlations between transit equity and network resilience?
2. Who are more likely to be affected by the lack of network resilience?

By answering the above research questions, this thesis will develop a methodology to measure the correlations between transit equity and network resilience, and thus identify population segments who are more vulnerable to transit service disruptions.

The remainder of this paper is structured as follows: Section 2 gives a review on existing literature regarding accessibility analysis and equity issues in transport planning. Section 3 presents the methodology proposed in this thesis, while Section 4 gives an overview of the study area. Section 5 outlines the results from this research. Section 6 discusses the methodology and results, and Section 7 gives a brief conclusion to this study.

2 Literature review

2.1 Interactions of transit accessibility and equity

2.1.1 Definitions of accessibility

Accessibility illustrates the relationship between activities and transportation systems. As Cascetta et al. (2013) mentioned, accessibility measures have been widely used in various land-use and transportation planning scenarios, such as integrated land-use and transport modeling, travel demand assessment, and efficiency assessments for transport projects. The concept of accessibility itself, however, remains abstract, and there have been various definitions for accessibility across the literature. As a widely accepted definition, Hansen (1959) defined accessibility as the potential of interaction opportunities, which measures the spatial distribution of activities, while considering the ability for users to overcome spatial separation. Under this definition, accessibility is calculated using the following equation:

$$A_i = \sum_j D_j c_{ij}^{-\beta} \tag{2.1}$$

where A_i is the accessibility for zone i, D_j denotes the amount of opportunities in zone j, c_{ij} is the time or cost to travel between nodes i and j, ans β is a cost sensitivity parameter to account for the impedance to travel, which, as summarized by Hansen (1959), depends on the purpose and importance of the trip, which explains different levels of willingness to travel depending on purpose.

Note that while a negative power function was used for the travel cost in the original Hansen Equation, Ingram (1971) and Geurs and van Wee (2004) also noted other functions used for the cost component during accessibility calculation, such as the normal function and the negative exponential function. Equation 2.2 shows the Hansen Equation using a negative exponential function, which, as Geurs and van Wee (2004) summarized, is more commonly used than other types of cost functions for reflecting travel behavior more closely.

$$A_i = \sum_j D_j e^{-\beta c_{ij}} \tag{2.2}$$

Another widely applied definition of accessibility is the density of activity opportunities within a certain generalized travel cost (such as time, distance, or monetary cost). As Wachs and Kumagai (1973) and Wickstrom (1971) explained, this definition can produce different accessibility values based on user characteristics such as modal choice, and thus reflect more towards specific demographics instead of providing a general synopsis. This definition could, for example, distinguish the reach of job opportunities between automobile and transit users, or between income levels, which indirectly affect the users' monetary travel budget. This is also one of the methods used by Breheny (1978) to measure accessibility, alongside the target opportunities method, which measures the cost required to reach the target number of opportunities. Using the contour measure mentioned above, Wachs and Kumagai (1973) proposed the following equation to compute accessibility:

$$A(T)_i = \frac{1}{100} \sum_j \sum_k P_{ijk} \frac{1}{100} E(T)_{ijk} \tag{2.3}$$

where $A(T)_i$ is the accessibility index for zone i within a travel time budget of T minutes, P_{ijk} is the proportion of population belonging to income category j and occupation category k, and $E(T)_{ijk}$ is the number of employment opportunities for residents in income category j and occupation category k accessible within T minutes of travel from zone i.

It should be noted that while Equation 2.3 was originally designed for computing an overall accessibility to employment opportunities, its nature as a weighted sum allows versatile usage, such as comparisons between automobile and transit accessibility, or between different population groups (Wachs & Kumagai, 1973). Also, while not mentioned in the study, this equation could theoretically be extended to apply to any type of opportunities that is not limited to employment by manipulating the variables within the equation.

Geurs and Ritsema van Eck (2001) decomposed accessibility into *network*, *spatial*, *temporal*, and *individual* components, in that while these components directly influence accessibility, the reverse also holds, i.e. demand and supply could be increased due to greater accessibility, and the components each influence one another. Whereas Geurs and Ritsema van Eck (2001) attributed the personal dimension of accessibility to the individual's needs, abilities, and opportunities, such component is often overlooked during planning and modeling processes, often only through sociodemographic data, despite having a heavy influence on the overall accessibility (Geurs & van Wee, 2004).

In a further study, Geurs and van Wee (2004) acknowledged the reality of accessibility measures focusing on particular aspects and could not be used to obtain a comprehensive view. The study thus classified accessibility measures into *infrastructure-based*, *location-based*, *person-based*, and *utility-based* perspectives. In the context of urban planning, location-based measures are commonly used to evaluate accessibility in a macroscopic or mesoscopic scale, taking supply of opportunities and travel costs into account. The equation by Wachs and Kumagai (1973), while being relatively easy to compute and interpret, fail to take personal perceptions into account, and is extremely sensitive to travel cost. Potential measures such as the Hansen Equation (Hansen, 1959; Ingram, 1971), on the other hand, while being harder to interpret, are well used in the literature for accounting the interactions between land use and transport. However, even with the cost sensitivity parameter that attempts to capture travelers' perception to trip purposes, it is still an objective value that could not explain a user's subjective perception overall to the transport system.

Therefore, an important indicator that has caught attention is the perceived accessibility, which is defined by Lättman et al. (2016) as the ease to live satisfactorily using the transportation system, which encompasses not only the accessibility to opportunities by the transport network, but also the access and egress process. It was proved that both objective and subjective indicators regarding service qualities like headways, access distances, passenger information and comfort, all contribute to the user's perceived accessibility alongside user demographics. Lättman et al. (2018) found significant deviations between objective and perceived accessibility, mainly because users tend to choose modes that satisfy their mobility needs, and thus both objective and subjective measures must be concurrently considered when evaluating accessibility. Thus, the paper acknowledged the need to consider the interactions between objectively and subjectively assessed accessibility in order to grasp a more complete understanding.

2.1.2 The first and last mile problem: accessibility to public transit

An important difference between public and private transport trips is the trip nature. Whereas private cars or taxis run on a point-to-point basis and thus offer a near door-to-door experience, this is rarely true for public transit where stops are fixed. Thus, access and egress distances, also known as the *first and last mile problem*, which are vital to overall accessibility by transit and in turn ridership, cannot be neglected during accessibility analysis. One of the performance indicators for transit services is the proportion of population served (Fielding et al., 1978), which depends on the service area around stops. As El-Geneidy et al. (2014) and Zhao et al. (2003) explained, access and egress distances directly affect the catchment area and thus the proportion of population accessible to transit networks. In accessibility analyses, it is common to assume access and egress distances to be 400 meters for bus stops (Zhao et al., 2003), and 800 meters for rapid transit (Alshalalfah & Shalaby, 2007). Yet, it should be noted that these are only generalized benchmarks and do vary depending on characteristics of the transit system and built environment

(Alshalalfah & Shalaby, 2007; El-Geneidy et al., 2014; Sarker et al., 2020), as the heterogeneous nature of transit stops and networks, and their locations with respect to the built environment, mean that benchmarks must be adapted accordingly for each case, such as in the case of Munich (Sarker et al., 2020), where walking distances between 1.0 and 1.5 kilometers were observed at suburban stations.

Studies have proved the negative impact to public transport demand caused by longer access and egress distances to transit stops. Mode choice models often weigh access and egress times heavier than in-vehicle time (Qin et al., 2023), which highlights the perceived inconvenience of walking during access and egress than the time spent in-vehicle. The emphasis on direct, quick walking routes by pedestrians also implies the users' top priority to minimize access and egress times (Alshalalfah & Shalaby, 2007).

Ewing and Cervero (2010) used various studies to test the impact of stop accessibility on mode split by analyzing the elasticity values regarding transit and private car trips. Positive elasticity values were found for private cars while negative ones were recorded for public transit. This implied users are more likely to use private over public transportation as access and egress distances lengthen. It was also found that despite inelastic correlations in general between trips and built environment, the paper did acknowledge the potentially large effect on travel when built environment factors are combined. However, the authors agreed that stop accessibility contributes to walking and transit usage, which are seen as complementary modes. The relatively high elasticity of intersection densities with respect to both walking and public transport is also noteworthy, primarily because this enhances walkability through shortening walking distances, and also provides more routing options, which eventually enhances the street network's resilience in that diversions can be made more easily.

Accessibility to the transit system, which refers to the opportunity of using the system, is often used as a target indicator in transit service provision, and this is associated with ridership (Murray et al., 1998). Daniels and Mulley (2013) demonstrated modal differences in walking as access and egress modes to transit, and showed an inverse relationship between access and egress distances and the resulting public transit trips traveled. Passengers are more likely to walk longer to access transit when the transit trips are longer, or when stops are spaced further apart, as reflected in the longer mean access distance to rapid transit than to buses. This also reflects the typical travel behavior in that passengers primarily traverse short distances by buses, and longer distances by rail. Even so, the general hypothesis of decreasing transit usage as access distances lengthen still holds true. Other studies regarding access distances to public transit also agree on this hypothesis, such as Zhao et al. (2003) where the vast majority of access distances recorded were under 500 meters, and transit use displays a diminishing trend with longer access distances.

Meanwhile, research has also shown dependence between transit accessibility and service characteristics such as headways or service areas. Alshalalfah and Shalaby (2007) have showed wider catchment areas for more frequent services, as shorter headways reduce waiting times and are thus more attractive to passengers, resulting in users willing to walk longer to reach these services. Modal differences in access distances are common due to distinctive characteristics between each mode. O'Sullivan and Morrall (1996) concluded longer access distances to light rail transit than buses and thus a LRT stop could potentially capture twice the passengers compared to bus stops. This could be attributed to the LRT's higher running speeds and its resulting further reach within the same time budget. Also noteworthy is the elasticity between waiting time and accessibility, in which a study had shown longer access distances as services operate more frequently and passengers experience shorter waiting times at stops (El-Geneidy et al., 2014). The same study also pointed out the influence of trip characteristics on access distances, in which transfers reduce the likelihood for users to walk longer distances due to the additional walking penalty involved during transfers. Additionally, walking distance during access and egress seems to be less relevant for longer in-vehicle trips, possibly as an effort to minimize the overall travel time.

A study by Sarker et al. (2020) in the metropolitan region of Munich, Germany also proved these hypotheses true, in that users generally walk longer to rapid transit than to buses or trams, which is consistent with the findings of O'Sullivan and Morrall (1996) regarding modal differences on access distances, where faster modes tend to have wider catchment areas than slower ones. It also found that stations in less dense areas (mainly in the suburbs) tend to have wider catchment areas, and thus showing a tendency of longer access and egress distances as density decreases. Another takeaway from the study is the emphasis on shortest walking paths by users, in line with other studies like Alshalalfah and Shalaby (2007), Ewing and Cervero (2010), and Qin et al. (2023), which found disutilities in access and egress times when compared to in-vehicle time.

2.1.3 Transit accessibility issues for underprivileged population

Whereas public transport should ideally benefit across all population segments, research has otherwise proved the reality of inequalities where underprivileged population such as those under poverty are more likely to endure the impacts than benefits. Keeling (2008) criticized the lack of focus on social equity aspects in transport planning, as planners emphasized on spatial analysis.

As Litman (2002) defined, transportation equity could be differentiated by how resources are distributed among the population segments. While *horizontal equity* (or *fairness*) is to distribute resources equally among all users, this does not take individual disadvantages into account. In a horizontally equitable system, policies do not favor particular user groups over one another as they aim to split resources or benefits equally regardless of social status. On the other hand, *vertical equity* (also known as *social justice* or *social inclusion*) concerns the impact distribution, and hence policies are designed to favor underprivileged users to compensate societal inequalities overall. As Delbosc and Currie (2011) noted, there is a conflict of perspectives in public transport planning, namely the "mass transit" paradigm versus the "social transit" paradigm, which stems from whether the quantity of users transported or the user groups should be prioritized.

Martens et al. (2019) considered three major aspects when developing equity measurement indicators: the benefits and burdens themselves, the population segments over which the impacts are distributed, and a clear conception of an equitable distribution. Studies on transport equity have so far included transport infrastructure and service supply (Ahmed et al., 2008; Delbosc & Currie, 2011), travel costs and subsidies (El-Geneidy et al., 2016; Pucher, 1981), or access to social or economic opportunities such as employment (Guzman et al., 2017; Neutens et al., 2010). Policy changes or interventions very often result in changes in accessibility, which explains why it is commonly used as an indicator during equity analysis. Land and property values in many European cities, including Munich, are higher in the city center and decrease as properties are located further away, as a result of high accessibility (especially by transit or walking) to amenities in the central areas (Brueckner et al., 1999; Kinigadner et al., 2016; Langer et al., 2023).

Socioeconomic characteristics provide valuable insight to the population composition and travel behavior, and thus the impact of socioeconomic statuses on transport planning cannot be neglected. Stead (2001) argued that socioeconomic factors such as income, employment status or car ownership often play as much role as land-use in explaining users' travel behaviors. Meanwhile, Rosenblatt and DeLuca (2012) found heavy reliance on public transit among the low-income population, and accessibility by transit was found to be a decisive factor during relocation. Similarly, Dong (2017) agreed on the transit reliance issue among underprivileged population, which could become an issue if transit-oriented development (TOD) results in higher housing costs.

The high land values associated with highly accessible amenities in the city center mean that, in general, the low-income population is more likely to reside further away from the city center (Brueckner et al., 1999). This results in longer trips and in turn higher costs (both temporal and monetary) for underprivileged residents to access opportunities that are centralized in the city. Dixit et al. (2021) also added that the problem could further be exacerbated by the modal differences in accessibility, which is accounted for by the cost function input in the Hansen Equation, where accessibility inevitably decreases as the travel cost rises.

The importance of equity in public transport, particularly for disadvantaged population groups, has been frequently discussed in scientific context. An important aspect in this relationship is the notion of social exclusion, which encompasses a set of social problems associated with societal structure fragmentation, declining societal participation, and increasing deprivation among particular population segments (Bocarejo S. & Oviedo H., 2012). By the definition of Burchardt et al. (1999), residents in a particular society who cannot or do not participate in the society's normal activities are defined to be socially excluded. Madanipour (2015) meanwhile, emphasized on the spatial dimension and defined social exclusion as a multidimensional process that combines different forms of exclusion in terms of political, social, economic, and cultural processes, which ultimately result in acute forms of exclusion with spatial manifestation in particular neighborhoods. Kenyon et al. (2002) included a mobility dimension into social exclusion, which is defined as the process by which inhabitants are inhibited from executing the above functions in society as a result of reduced accessibility to opportunities and insufficient mobility.

As Kenyon et al. (2002) noted, mobility-related social exclusion does not necessarily relate to public transit service coverage, as service or infrastructure might not take disadvantaged population into mind, thus excluding such potential users out of the system. This relates back to the concept of perceived accessibility (Lättman et al., 2016; Lättman et al., 2018), since whereas the objective accessibility for the neighborhood might be adequate on a coverage level, the lack of consideration of underprivileged users means that, even if the system could theoretically meet the users' mobility needs, it is unlikely that such users could use the system to satisfy their daily lives, and by this they could be seen as socially excluded. Moreover, mobility-related exclusion affect inhabitants both in the neighborhood and individual scales, and was found to reinforce social exclusion in other dimensions, especially in poor areas where inhabitants already experience multifaceted social exclusion repercussions, and are often poorly served by public transport, while barriers to transit use can affect perceived accessibility (Kenyon et al., 2002).

Grengs (2001) identified some common household characteristics which are more likely to depend on transit, such as low-income, disabled, or migration backgrounds. Likewise, an analysis on travel surveys in Germany and the USA by Buehler and Pucher (2012) discovered that unemployed and low-income households are more likely to rely on public transport. Whereas the older population are more likely to use transit than adults, the study also acknowledged a significantly higher share of transit trips among the German younger population than other age groups, a phenomenon which is less obvious for their USA counterparts. These users are less likely to have access to automobiles and therefore rely on public transit to satisfy their needs and are therefore known as captive riders. Whereas these users show the greatest demand for transit services, there exist areas with low transit service and yet a high proportion of captive riders exist. Such areas are defined by Jiao and Dillivan (2013) as transit deserts, given the inadequate transit supply with respect to the demand from captive riders.

Competition in housing markets due to scarcity is a common phenomenon in metropolitan regions. As Sterzer (2017) explained, rising real estate prices are commonly observed in the housing markets in metropolitan regions, and properties with higher accessibility to and by public transport, mostly in the city center, tend to have higher prices, while those further out in fringes or suburbs tend to be more affordable. Moreover, as improvements to public transit network enhance accessibility to the service areas, land use changes are commonly seen as a consequence. One common phenomenon is the displacement of underprivileged population through gentrification processes, where increasing land values due to improved accessibility result in a shift in the affordable demographics.

Bajic (1983) explained that the higher housing costs for new housing developments is due to the reduced generalized commuting cost through rapid transit in walkable distances, which theoretically would result in constant budget for housing and commuting. While "new build gentrification" as defined by Davidson and Lees (2010) is mostly due to land use changes themselves such as during redevelopment, the definition could be extended to transit services, which induce land use changes and redevelopments in their service areas due to improved accessibility. Should gentrification occurs, low-income residents in these new service areas are most likely displaced from the district. While there exists a proportion of such underprivileged residents that struggle to stay, a tendency of population replacement and displacement still exhibits (Newman & Wyly, 2006). Meanwhile, a study on the impact towards underprivileged population along a rapid transit corridor as a result of revised transit-oriented development (TOD) zoning guidelines has warned of population displacements due to gentrification, when such accessible areas are being redeveloped (Jones & Ley, 2016).

Likewise, Chava and Renne (2022) also compared gentrification cases due to TOD in some North American metropolitan regions. Whereas gentrification was observed in general throughout the network, TOD neighborhoods are gentrified to a higher extent due to their high walkability and mixed land use. Population mix in these areas also altered significantly, suggesting that the gentrification disproportionally affects communities near transit stops than those that are less accessible to public transit, and as the underprivileged population is displaced to less accessible areas, they lose reliable access to job and service opportunities through transit services. By depriving the disadvantaged population their access to transit services through displacement to less accessible locations, public transportation fails to meet the mobility needs of the intended population in its service areas. The failure to consider population displacement due to transit-induced gentrification also means that public transit cannot address the demand of passengers across different demographics, especially when underprivileged residents are more likely to rely on transit.

Referring back to Sterzer (2017), who conducted a study on mobility behavior with respect to housing market in the metropolitan region of Munich, it was found that some respondents were displaced from Munich proper to its suburbs, especially due to high rents in the city, which made properties in the city no longer affordable for them. This illustrates the effect of population displacement as a result of excessive demand in the housing market. While residents value adequate accessibility, the objectives of maximizing accessibility and minimizing rent are often conflicting in a way that accessibility is sacrificed for money.

2.1.4 The issue of circuity in public transit

Circuity within a public transportation system also contributes to transit accessibility and the reach of transit when compared with automobiles. The established method to compute circuity (detour index) in network theory is by the following equation (Barthélemy, 2011):

$$Q(i,j) = \frac{d_R(i,j)}{d_E(i,j)} \tag{2.4}$$

where $Q(i,j)$ is the circuity index from node i to node j, $d_R(i,j)$ the distance traversed along the network edges (network mileage), and $d_E(i,j)$ denotes the displacement (euclidean distance or *as the crow flies*). Smaller circuity values indicate lower detours for a given origin-destination (O-D) pair between the nodes, and thus imply more time-efficient trips. The node accessibility for node i in an N-node network, $\langle Q(i)\rangle$, can then be derived as an average of all the circuity values from the concerned node using the following equation:

$$\langle Q(i)\rangle = \frac{1}{N-1}\sum_j Q(i,j) \tag{2.5}$$

This can be used as a benchmark to assess the ease or efficiency to travel from the specific node (Crucitti et al., 2006). It is worth noting that Barthélemy (2011) refers to this mean value as the node accessibility. While this does provide insights on the ease to reach the node, it only considers the network without taking socioeconomic aspects such as employment opportunities into consideration. Therefore, this is merely an infrastructure or network-based indicator and plays a minor role on equity itself.

Studies have explained the effects of circuity indices towards transit network efficiency and mode choice, including mode share differences across O-D pairs due to different circuity values across modes and thus resulting in varying accessibility levels for locations or users. Transit accessibility depends on both circuity indices for both road and transit networks due to different extents of right of way exclusivity among modes.

It was also noted that higher automobile circuity would result in a modal shift to transit due to relatively better transit accessibility and driving becoming less efficient (Huang & Levinson, 2015).

The circuity and accessibility correlation can be especially obvious with meandering public transport routes or services, as transit services are often faced with the conflicting objectives to maximize both coverage and ridership (Walker, 2012b), and the easiest way to maximize coverage is to operate circuitous routes to serve as many locations as possible in one go. This is most commonly seen in basic lifeline services in low-demand rural areas where even a medium density service cannot be justified. As Walker (2012a) explains, circuitous routes and deviations from direct routings contribute to deviations from directness, and thus higher circuity values, because the route deviates more from the displacement or the shortest possible path. Such circuitous routes, while providing direct services between intermediate points, eventually defeat the purpose of providing quick end-to-end service, especially when more direct services operate in parallel. Even when no parallel direct services run, circuitous transit services would result in considerably high circuity values compared to automobiles, thus fail to attract passengers. Referring back to Huang and Levinson (2015), such routes with high circuity values are inefficient and thus weakens accessibility, especially when travel times lengthen and thus points of interests can no longer be reached within a specified time budget with a more circuitous route.

Radial transit networks, in which lines radiate outwards from a central location, could pose additional challenges to accessibility when using transit. The lack of tangential crosstown connections mean that passengers taking such trips are forced to travel into and out of the city center, often with transfers and long trip durations (Saidi et al., 2016). Studies like Laporte et al. (1997) have been aware of deficiencies caused by radial networks and therefore suggested a ring-radial structure with loop lines encircling the city in addition to radial lines to ensure better connectivity between areas, and such layouts have proven to enhance network efficiency, which accounts for lower overall circuity. This can be important in metropolitan regions like Munich where a trend of metropolization and decentralization could be observed, and more employment opportunities are being relocated out of the city center (Wenner et al., 2020), which would generate more tangential commuting demand.

Another problem with transit is the necessity to transfer between services. As public transport networks are designed to balance directness, ridership and coverage, direct one-seat rides for many O-D pairs are often not possible. Transfers are often perceived negatively by passengers, in some cases even more severe than access and egress times. Researchers have developed methods to incorporate transfer penalties into mode choice models as a result of such disutility. Horowitz and Zlosel (1981) decomposed the transfer disutility into two components: a constant transfer penalty independent of the time taken due to the transfer itself, and the time taken during the process, which is often multiplied by a conversion factor into in-vehicle time equivalents when computing generalized travel costs.

The study on transfer penalties by Cascajo et al. (2017) highlighted poorer passenger perceptions as more transfers are required. In their model, walking and waiting times during transfers are much more negatively perceived for trips requiring two transfers than those with one transfer, and the penalty constant also increases with an additional transfer, thus proving the disutility of transfers. The paper also noted that passengers tend to avoid transfers, even in the ideal situation with zero walking and waiting time, something that is reflected through the penalty constant, and so it can be deduced that passengers may prefer a circuitous one-seat ride to a more direct trip requiring a transfer, even if the actual time taken on both paths are similar.

2.1.5 Circuity issues and transit equity

Dixit et al. (2021) and Karaaslan and Mert Cubukcu (2023) pointed out as services are centered at areas with more affordable inhabitants, underprivileged users who are more likely to be displaced to the outlying edges often need to take detours to reach their destinations, and such circuitous journeys often mean greater trip costs. These case studies proved correlations between socioeconomic statuses and transit circuity, indicating low-income users are more likely to take circuitous trips, which implies transit inefficiencies in low-income neighborhoods. As Galster and Killen (1995) explained that higher income residents are more likely to access public services, income and thus sociodemographic status could determine accessibility to public transit. Transit network inefficiencies in areas populated by underprivileged residents are therefore clear signs of supply and planning failure from an equity aspect through depriving them efficient transit services.

As explained by Pucher and Renne (2003), transit planners often take underprivileged captive riders such as low income or ethnic minority residents for granted, and thus mostly focus on attracting more affluent users in the middle class. The diversion of subsidies and resources towards the middle class thus often resulted in poor, rudimentary services for underprivileged riders. Referring to a public transportation network's conflicting objectives to maximize both coverage and ridership, trade-offs are inevitable as higher coverage comes with the expense of high circuity values and thus longer travel times, whereas direct services that minimize travel time are more likely to attract passengers (Walker, 2007, 2012b).

The radial layout of Munich's rapid transit network, in which lines radiate from the city center, and is a result of the monocentric structure of the Munich Metropolitan Region, poses a challenge to accessibility by transit, in that the lack of robust tangential crosstown connections could cause long trip durations and distances, and these O-D pairs generally have high circuity values on transit (Saidi et al., 2016). With commuters being displaced to outer suburbs which are more affordable but less accessible by transit (Kinigadner et al., 2016; Sterzer, 2017), disadvantaged residents are being forced to take detours as a result of poor accessibility by transit. Moreover, the problem could be exacerbated by the fact that bus services in the suburbs are often meandering due to low demand (Walker, 2012b). Commuters residing in neighborhoods away from radial corridors would need to use these bus services as feeders to rapid transit in order to commute to the city. The combination of underprivileged population being displaced outwards, and the circuitous nature of transit services in outer suburbs, could contribute to high circuity values for trips undertaken by the disadvantaged population.

2.2 Resilience of public transportation networks

2.2.1 Overview of resilience analysis

As an essential component to maintain service during disruptions and provide alternatives to passengers, network resilience is frequently studied in transportation engineering. Reasonable alternatives should be considered during the planning process, especially on major routes, to ensure the network can be resilient enough to cater passenger demand, while taking account into the limited infrastructural and operational resources such as track capacities, rolling stock or personnel availability. While multiple definitions for resilience exist, a commonly accepted definition is the "4R" principle developed by the Multidisciplinary Center for Earthquake Engineering, which summarizes resiliency into four major components: robustness, redundancy, resourcefulness, and rapidity. While this is mostly used in research on rapid response following natural disasters in general, this can be extended to transport network in response to any foreseeable or unforeseeable disruptions. Resilient systems should be able to reduce failure probabilities, and should failures occur, systems should reduce consequences and be able to recover quickly (Bruneau et al., 2003).

Assessing redundancies and resilience in public transport networks require considering various elements both in the sub-networks and the entire network at large. Xu et al. (2015) emphasized diversity of travel alternatives and spare capacities as indicators, taking capacities of practical alternative routes into consideration. As passengers aim to reach their destinations as soon as possible despite the disruptions, it is important to consider whether alternative paths are feasible to the user by considering travel time or costs, and how the detour would prolong the trip. To account for the supply and demand interactions, the network spare capacity must also be considered to evaluate the effect of demand shifts to and absorption by other links. Malandri et al. (2017) utilized mode choice models to analyze the impact of disruptions to passengers, and showed that merely replacing a disrupted rapid transit line section with emergency buses, where no alternative services are available, could yield a worse outcome where passengers could experience more extreme discomfort. This implies nearby, parallel alternative routes contribute to higher resilience and better user experiences during disruptions.

An important concept related to resilience is the network connectivity, which is the ease to travel freely within the network, and reflects the density of transfers (Derrible & Kennedy, 2009). Highly connected networks are characterized by dense transfer opportunities, and thus a wider range of alternative trip paths. The lack of circumferential links in purely radial networks, including the one in Munich, could decrease the network connectivity as radial corridors are not connected with each other by rail outside the city, and could therefore be more prone to disruptions (Saidi et al., 2016). As radial networks are poorly connected outside the city, they demonstrate a lack of travel alternatives, which could become problematic during disruptions (Xu et al., 2015). Moreover, capacity in radial networks are ultimately constrained by the maximum capacity within the city center, such as in the Munich suburban network where the trunk line is already operating at capacity (Wenner et al., 2020), and thus it would be unlikely for other nearby corridors to have spare capacity to absorb demand from a disrupted line, even if passengers are willing to make detours to other corridors. Thus, radial networks are especially vulnerable to disruptions due to the lack of diversity in travel alternatives and spare capacity. Moreover, Mo et al. (2022) analyzed the impact of network redundancy on travel behaviors, and showed higher probabilities for passengers to continue using transit despite disruptions in a more resilient and redundant network. This is particularly true in multimodal networks, where passengers may switch to other modes to complete their trips. The paper also acknowledged the importance of user demographics, in that as low-income residents are more likely to use transit, a highly resilient public transport network is necessary to keep such captive riders mobile during disruptions. As Derrible and Kennedy (2009) analyzed, well connected networks are more accessible to passengers, and thus attract more ridership. This is an important observation, in that passengers might not travel at all during disruptions, and thus maintaining connectivity during disruptions is vital to keep users mobile.

While modal hierarchies are commonplace in multimodal and intermodal transportation systems and thus multi-modality is more of a complementary mechanism, these modes could substitute one another should disruptions occur. Thus, recent studies have acknowledged this interdependent nature and developed frameworks to assess multi-modal network resilience at large. B. Liu et al. (2023) assessed the network efficiency and concluded disruptions on one mode could significantly affect other modes as passengers use alternative modes and paths. Multi-modal networks complicate assessment due to passengers transferring between multiple modes, and the locations of such transfer nodes, as well as the network structure, also affect performance and resilience during disruptions. Interdependent relationships between modes are therefore vital when considering multi-modal systems. A study comparing network resiliencies in Hamburg (where the tram network was completely closed) and Munich (where the tram network was largely closed but then re-expanded), had showed the importance of modal capacity when considering network redundancy and resilience, and a huge gap between modal capacities could hinder resilience as capacities cannot be absorbed easily by other modes (Scheurer, 2016). The large gap in capacities between rapid transit and buses, as in the case of Hamburg, could be problematic when rapid transit lines are closed as buses need to cope with additional passenger influx from rapid transit, which could be alleviated by providing medium-capacity alternatives such as trams.

Jin et al. (2014) suggested further integrating bus networks with rapid transit systems on a local scale to provide higher resilience, including linking nearby stations on other services. While running buses or trams parallel to rapid transit might not be cost-effective on its own, when combined with services linking to nearby rail lines, network resilience could be enhanced by providing more travel alternatives to passengers, especially during disruptions. As shared mobility gains traction, there has also been a study on bike sharing to supplement public transit and showed the potential of such systems to enhance resilience of the entire network by diverting the transit demand away from fixed-route transit towards shared micromobility alternatives during disruptions (Cheng et al., 2022). While research on shared micromobility on transit resilience is still in its infancy, it has proved that bike or scooter sharing systems could function as alternative bridging modes to walking or motorized transport.

2.2.2 Role of network resilience in accessibility analysis

There has been ongoing research regarding the role of network resilience on public transit accessibility. During service disruptions, passengers need to take detours which result in longer trip durations and additional transfers, and the diversion of travel demand to other available paths often result in severe overcrowding. As a result from these effects, increased travel costs and decreased travel utility account for the deterioration of accessibility during disruptions (Chen et al., 2007).

As Sohn (2006) explained, distance or cost-based accessibility measures, such as the formula by Hansen (1959) do not necessarily account for the significance of individual links. In the context of network resilience, it is crucial to consider the link significance when analyzing the deterioration in accessibility during disruptions, as heavily-demanded links are more vulnerable to such deteriorations. Chang (2003) and Chang and Nojima (2001) developed indicators to measure the accessibility performance after an earthquake using accessibility ratios, a measurement which compares accessibility before and after the disruption caused by the earthquake. Meanwhile, Sohn (2006) approached the accessibility decay problem differently, using a difference rather than ratio to account for this. While this method simplifies calculations, it is used to analyze accessibility changes on a link scale, and cannot be easily adopted to the network scale. Moreover, Kim and Song (2018) developed an integrated accessibility and reliability measurement indicator to inquire the extent of network reliability and accessibility on local or global scales, and could infer possible underserved or unreliable locations.

3 Methodology

This thesis will utilize a straightforward methodology to develop objective indicators to measure accessibility decay and its impact towards disadvantaged population segments. Figure 3.1 depicts the research process during this thesis.

The methodology of this thesis first involves geospatial analysis where the reference point for each municipality is determined. Accessibility decay indices AR_i for municipalities are then computed based on travel time matrices, and are then weighted by the percentage of each population group considered to obtain the weighted accessibility decay index $I_{i,k}$. After that, a linear regression model is generated to test the significance of population compositions on AR_i.

3.1 Accessibility decay analysis

3.1.1 Geospatial analysis

Geospatial data for the study area, including the administrative boundaries to the municipal level, and the public transit lines within the study area, were obtained using OpenStreetMap data (OpenStreetMap contributors, 2023) through the QuickOSM plugin in QGIS, an open-source geographical information system.

The population centroid for each municipality, which indicates the center of the municipality weighted by population distribution, is computed using GIS and used as the reference point for the municipality. Compared to the geometric centroid without weighting, a population-weighted centroid takes population distribution and density into account, which in turn reflects the relative demand concentration within each municipality. This is important as population is concentrated at settlements built along the transport infrastructure (roads or railways) rather than equally spread across the municipality.

Despite the use of population centroids over geometric centroids, there exist cases where settlements are dispersed and thus results in a population centroid out of nowhere without road connection. Therefore, a correction step is required to snap the centroids to the nearest road such that the point could be accessible by pedestrians. This step facilitates accessibility analysis using R5R, which considers all trip aspects from access to egress, and not only the in-vehicle time.

3.1.2 Accessibility decay index

To answer the first research question on developing objective indicators between disadvantaged users and network resilience, an accessibility indicator first needs to be developed. The calculations for accessibility follows the gravity model using the Hansen Equation (Geurs & van Wee, 2004; Hansen, 1959; Ingram, 1971). Moreover, as per the definition of Kim and Song (2018), accessibility in the context of transit networks refers to the ease to complete a trip using the network. Therefore, O-D passenger flows using transit services are needed to account for demand variations.

To obtain correct travel times, R5R requires a GTFS data set which contains the transit services and their schedules. The General Transit Feed Specification (GTFS) is an established data exchange format for scheduled transit operations through incorporating pre-planned schedules into the data set. This format has been applied for transit routing and accessibility analysis (Wessel & Farber, 2019). The O-D travel

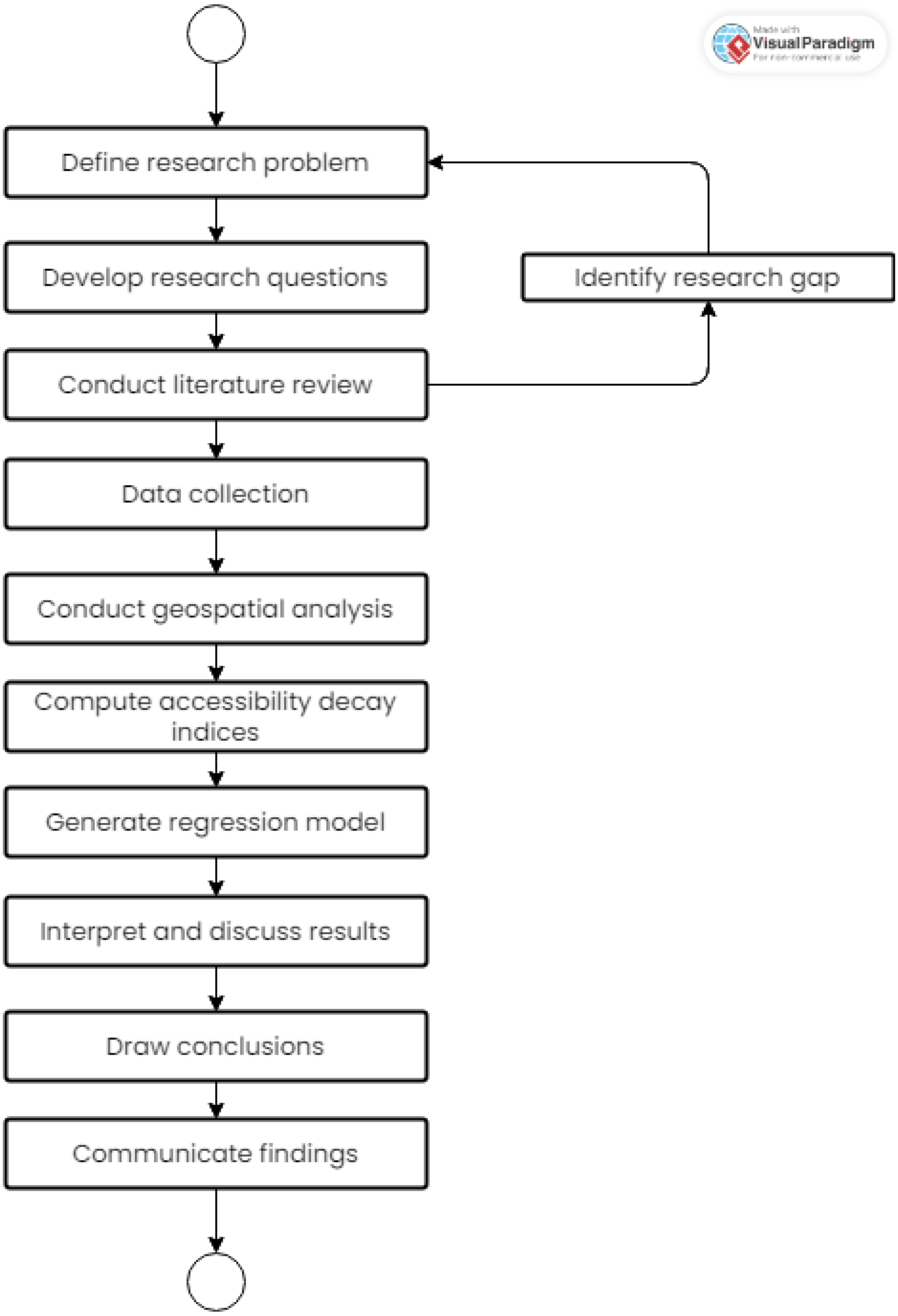

Figure 3.1 Flowchart for the research process

times are then calculated using R5R (Pereira et al., 2021) in the statistical programming language R and based on the Rapid Realistic Routing on Real-world and Reimagined networks (R5) routing algorithm, which is developed for and mainly used in public transit network analysis (Conway et al., 2018).

Due to the specification of a departure time in R5R, waiting time is included in the travel time matrix. This component, however, should not be considered as the waiting time depends on departure time, while the in-vehicle, access, transfer, and egress times are all independent of the departure time. Therefore, before using the travel time as costs in Equation 3.1, waiting times must be subtracted from the total trip duration.

Accessibility deteriorates as services are disrupted and links or nodes become unusable. Thus, an important indicator in this study is the accessibility decay index which describes the extent accessibility is deteriorated. The methodology for developing the accessibility decay index in this paper mainly follows the one developed by Chang (2003), which was used to analyze accessibility performances on the railway network in Kobe, Japan, following infrastructural damages caused by an earthquake in 1995.

The standardized indicator of decay index is derived from accessibility ratios, which are obtained using the following formula:

$$AR_i = \frac{\sum_j w_{ij} c_{ij,disruption}}{\sum_j w_{ij} c_{ij,normal}} \tag{3.1}$$

where c_{ij} is the travel time cost along the quickest path, and w_{ij} is the weight of destination j with respect to origin i. Note that while AR_i is a nodal measurement, these values can be averaged to obtain a global value for a particular area or the entire network. For an area with N nodes, the areal average accessibility AR_{global} could then be calculated using the mean value of all accessibility values using the following equation:

$$AR_{global} = \frac{1}{N} \sum AR_i \tag{3.2}$$

The accessibility ratio AR_i denotes the extent of reduction in accessibility during disruptions. AR_i takes a minimum value of 1 which denotes transit service remains intact, and increases as accessibility deteriorates.

3.1.3 Accounting for underprivileged population groups

As Martens et al. (2019) noted, population segments over which the impacts are distributed must be considered when developing indicators to measure transport equity. Hence, whereas variables from the supply and demand aspects like travel costs and O-D demand shall be considered (El-Geneidy et al., 2014; Guzman et al., 2017; Neutens et al., 2010; Pucher, 1981), the effect of varying extents of impact distribution towards different population segments also needs to be considered. To capture the impact of low network resilience towards underprivileged population segments, a weighted decay index I is proposed as a measurement indicator. This indicator could be used on both local and global scales depending on the objective of measurement. The weighted accessibility decay index I for a particular population group k for a zone i could then be computed using the following equation:

$$I_{i,k} = AR_i P_{i,k} \times 100 \tag{3.3}$$

where $P_{i,k}$ is the proportion of underprivileged population group k in node i. As greater AR_i values imply poorer transit service, higher $I_{i,k}$ values denote higher vulnerability and in turn a lower resilience towards disruptions due to poorer services for the population group k, while 100 is a multiplication factor to account for percentages in population composition, as the population proportions are multiplied as decimal values. As this study aims to investigate which population segments are more vulnerable to accessibility decay in case of transit service disruptions, the indices are aggregated on a spatial level and compared by the corresponding population group at this step, which can be done using the following formula:

$$I_{k,global} = \frac{1}{N} \sum_i I_{i,k} \tag{3.4}$$

3.2 Correlation analysis

3.2.1 Linear regression analysis

To further examine the correlation between network resilience and equity, AR_i is tested against the proportions of the focus underprivileged population segments by constructing a multivariate linear regression model using R. The regression equation is shown below in Equation 3.5, and the variables used in the model are summarized in Table 3.1:

$$AR_i = a_0 + a_{radial} x_{radial} + \sum_k a_k x_k \tag{3.5}$$

Variable	Explanation
AR_i	Accessibility ratio for municipality i
a_m	Coefficients of variable m
x_k	Proportion of underprivileged population group k, standardized
x_{radial}	1 if served by radial lines, 0 if else

Table 3.1 Coefficients used in linear regression model for computing accessibility deterioration factor

The inclusion of x_{radial}, the categorical variable that determines whether the municipality is served by a radial line from the city, is needed, as these municipalities themselves have the advantage of being more accessible due to the direct connection to the rapid transit network.

However, before generating a linear regression model, the population composition percentages x_k, which are used as the inputs to the model, must first be normalized to minimize the influence of different ranges across the population groups. Normalization is done such that the range of the data set is between 0 and 1. This is done through the following formula:

$$X_i = \frac{x - \min(x)}{\max(x) - \min(x)} \tag{3.6}$$

By generating a linear regression model, the coefficients for each independent variable could be obtained, and thus the extent of how each population segment affects network resilience could be known. Thus, the second research question of who are more likely to be affected could be answered.

3.2.2 Hypothesis testing

Literature has found that transit accessibility for underprivileged population segments is lower than for more affluent residents, such as due to property values. These users are more likely to reside towards the outskirts of the metropolitan region, which are less accessible. By virtue of being less accessible, it is also understandable that there are limited travel alternatives, and thus during disruptions, accessibility would be further hindered by the low resilience and higher vulnerability towards disruptions.

Therefore, hypothesis testing will be performed by proposing the following null hypothesis **H0**:

H0: Composition of all population groups are not significant in affecting network resilience through the AR_i value.

The corresponding alternative hypothesis **H1** is then:

H1: Composition of at least one population group affects the transit network resilience through the AR_i value.

The purpose of this hypothesis test is to test whether population compositions would affect the network resilience of a municipality. Statistically significant predictors of population compositions could indicate the corresponding population groups are more vulnerable to transit service disruptions, and thus further validate the second research question.

4 Case study

4.1 The study area

The Munich Metropolitan Region is one of the largest metropolitan regions in Germany, spanning over 25,000 square kilometers and is home to about 6 million residents. While the metropolitan region itself and thus Munich's wider commuter belt reach as far as the regional centers of Augsburg and Ingolstadt, and the scenic counties of Garmisch-Partenkirchen and Traunstein, this study will focus on the inner suburbs as they tend to exhibit higher commuting demand to Munich (Guth et al., 2011), especially in the case to the north and west where the outer suburbs double up as suburbs of Ingolstadt and Augsburg, respectively alongside Munich.

The inner suburban area in this thesis is defined as the service area of the Munich S-Bahn (suburban rail). This area, as shown in Figure 4.1, encompasses the city of Munich and the counties immediately surrounding it, i.e. the counties of Munich, Dachau, Freising, Erding, Ebersberg, Bad Tölz-Wolfratshausen, Starnberg, and Fürstenfeldbruck. Also included in the inner suburban area are the municipalities of Geltendorf (Landsberg am Lech county), Holzkirchen, Otterfing, and Valley (Miesbach county), which are the outer edges of the S-Bahn network.

4.1.1 Public transport network in the Munich inner suburban area

Whereas an extensive public transportation system with rapid transit, trams, and buses exist within the city of Munich itself, the transit network in the Munich suburban area exhibits a monocentric radial structure centered at the city of Munich with only a handful of tangential connections, which reflects the largely monocentric structure of the Munich Metropolitan Region. With a daily ridership of up to 0.95 million, the Munich S-Bahn, Munich's suburban rail system, is considered to be the backbone of the inner suburban traffic connecting the city with its suburbs. Despite the radial alignment of the rail network, there has been improvements on providing tangential crosstown connections through express bus routes (colored blue in Figure 4.1) in the immediate suburban areas encircling the city of Munich, thus offering attractive alternatives to S-Bahn connections, which require passengers traveling all the way into the city center in order to transfer to other branches. These express bus services often connect with the S-Bahn or subway at transit nodes besides providing regular tangential connections, thus further enhancing regional connections.

Within the suburbs, local and regional buses coordinated by the Munich Transport and Tariff Association (MVV) act as feeders between local communities and S-Bahn and express bus services. These local bus services, especially those operating in sparsely populated areas, often operate at lower frequencies (often every one or two hours), or even only a handful of departures per day. While such low supply levels might reflect the low demand in their service areas as a result of low population densities, the drawback is that long headways negatively impact transit accessibility in the temporal aspect, as the buses are only available during pre-determined times, and transit riders therefore must schedule their activities around the bus departures. As Geurs and Ritsema van Eck (2001) explained, the temporal component of accessibility involves both the availability of the opportunities during different times, as well as the times when users can access the opportunities. In this case, the buses are not available all the time, and thus despite other opportunities such as employment in the city could theoretically be accessed throughout the day, passengers in the underserved areas are ultimately bounded by the bus schedules and such the times

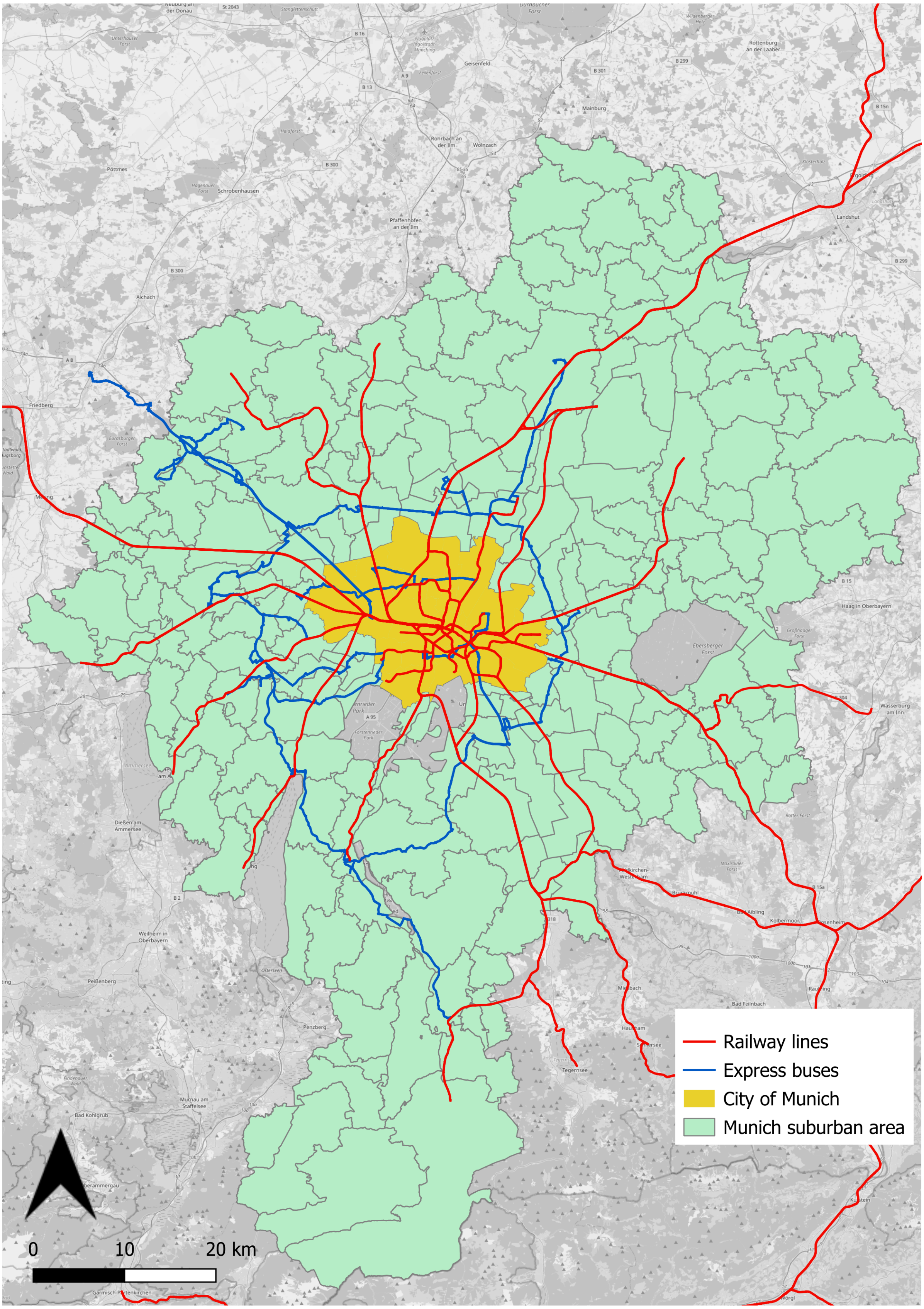

Figure 4.1 Map of the Munich inner suburban area and the major public transit lines (own work, using data from OpenStreetMap contributors (2023))

to access other opportunities are limited. While S-Bahn and tangential express buses operate regularly throughout the day (normally every 20 minutes), which allow passengers to basically turn up and go without excessive waiting, the sparse service on the local level eventually hinders the users' temporal accessibility when the extra transfer and limited number of trips must be considered in the trip chain.

4.1.2 Target population segments

Section 2.1.3 summarized some demographics that are more likely to rely on public transit, including youth, elderly, low-income, disabled or migration backgrounds (Buehler & Pucher, 2012; Grengs, 2001). The Mobilität in Deutschland (MiD), the German nationwide travel survey which was last conducted in 2017, also provided some valuable insights on transit-dependent population segments in Germany. The young population such as school pupils and university students dominates transit usage in Munich and its suburban area. However, as reported by the MVV (2020), whereas high-income residents use less transit, there were no significant differences in transit usage between low-income and middle-class populations.

Considering the above transit-dependent user groups and data availability, this study would include the following population segments into analysis: youth (age 18 to 30), elderly (age 65 or above), low-income, severely disabled, and unemployed. The population and demographic data for the study area at the municipality (Gemeinde) level was obtained from the Statistical Office of Bavaria (Bayerisches Landesamt für Statistik, 2019). As the latest population data regarding income is in 2019, all relevant population data are accurate as of 2019 to synchronize the reference timeframe during analysis. Table 4.2 gives a summary of demographic composition in each county, while Figures 4.2 to 4.6 depicts the municipalities where such population groups are more concentrated.

Regarding the low-income population, the net personal income is used to determine whether a person falls into the low-income category, and this upper threshold is 60 percent the average personal net income (Brenke, 2018). Based on the average income provided by Statista (2023), the average personal net income in 2019 was about 23,700 euros, which means the upper threshold for low income would be 14,220 euros. Hence, the low-income population encompasses those whose net income were lower than 15,000 euros to account for stratification. Note that low-income residents are compared against the total number of taxpayers, as non-working population essentially receive zero income and so if they are included, the indicators might become biased.

Population segment	Mean	St. Dev.	Min	Max
Unemployed (%)	1.0	0.2	0.3	2.1
Disabled (%)	6.7	1.3	4.5	14.8
Low-income (%)	20.3	2.8	15.9	25.7
Older (%)	18.6	3.2	10.9	27.8
Younger (%)	13.4	1.7	10.2	24.8

Table 4.1 Statistical indicators for percentages of population compositions (N=166)

There are some interesting observations from Figures 4.2 to 4.6. Municipalities with S-Bahn connections in general have higher concentrations of low-income population than those without direct connections to Munich. These municipalities also have higher concentrations of unemployed population. Disabled people are more likely to reside closer to Munich than further out. The counties of Freising and Erding exhibit a higher concentration of young population than others, while Fürstenfeldbruck, Starnberg and Bad Tölz-Wolfratshausen counties towards the south and west have higher concentrations of older residents.

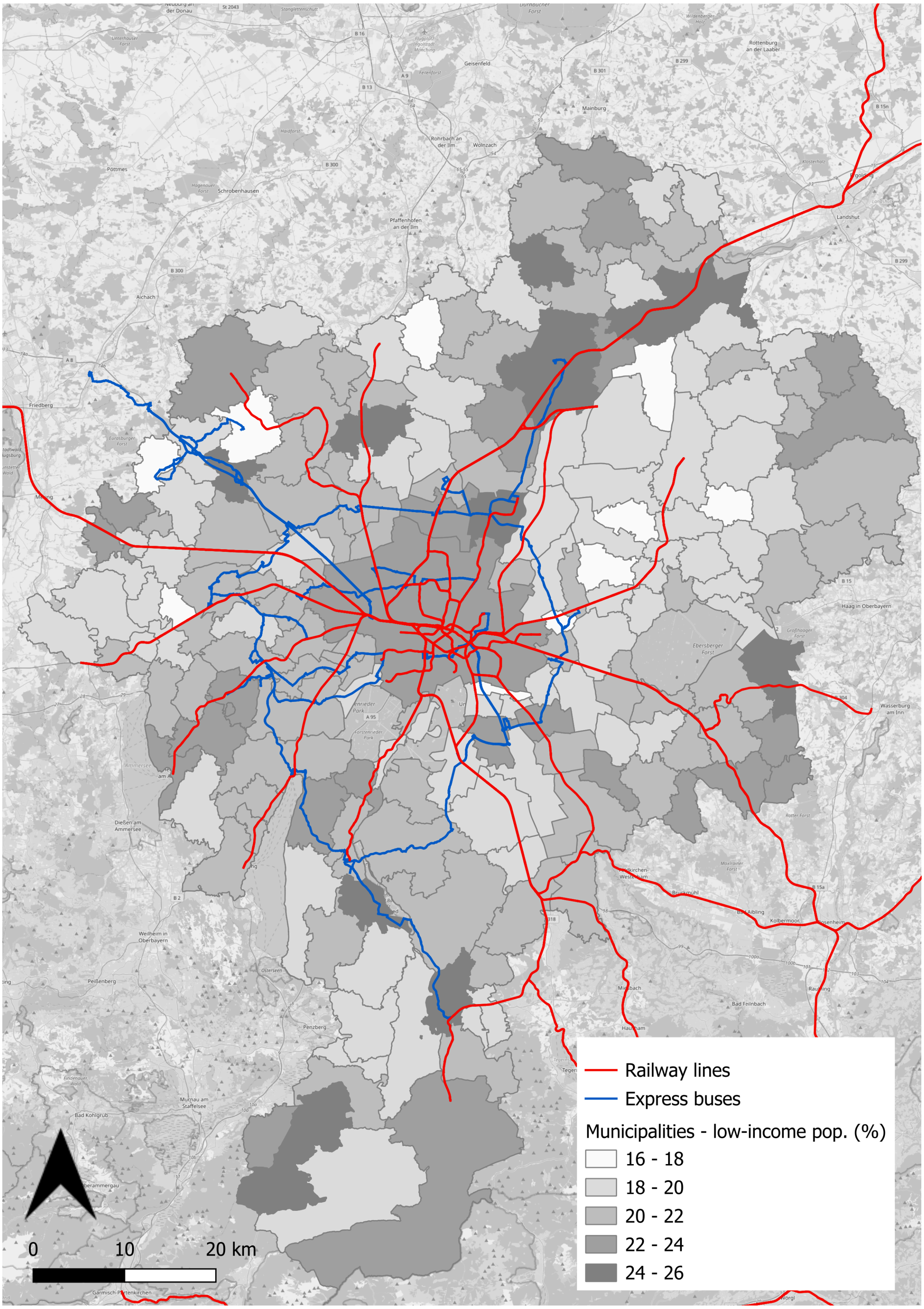

Figure 4.2 Distribution of low-income population density (in percentages) of municipalities in the study area

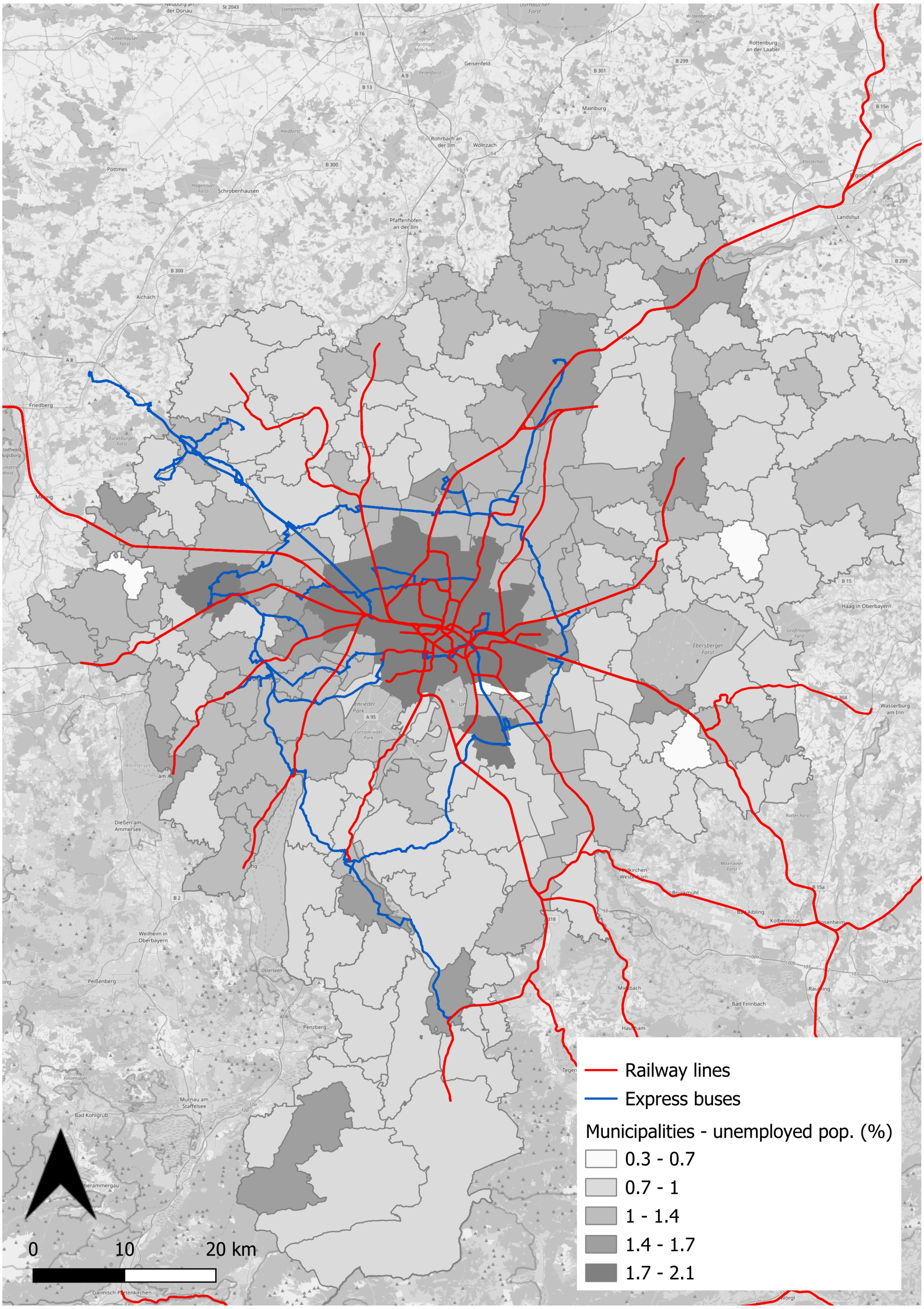

Figure 4.3 Distribution of unemployed population density (in percentages) of municipalities in the study area

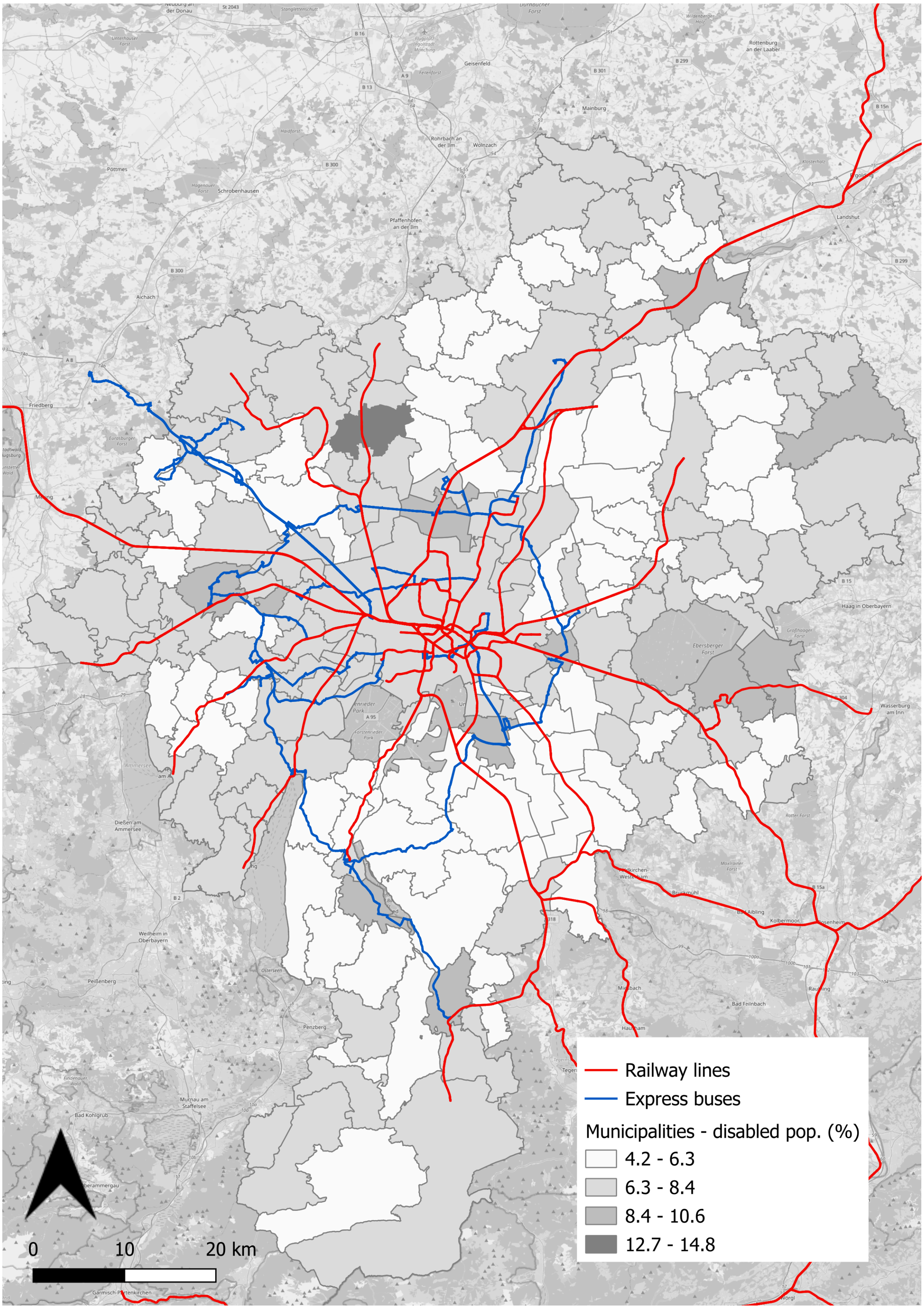

Figure 4.4 Distribution of disabled population density (in percentages) of municipalities in the study area

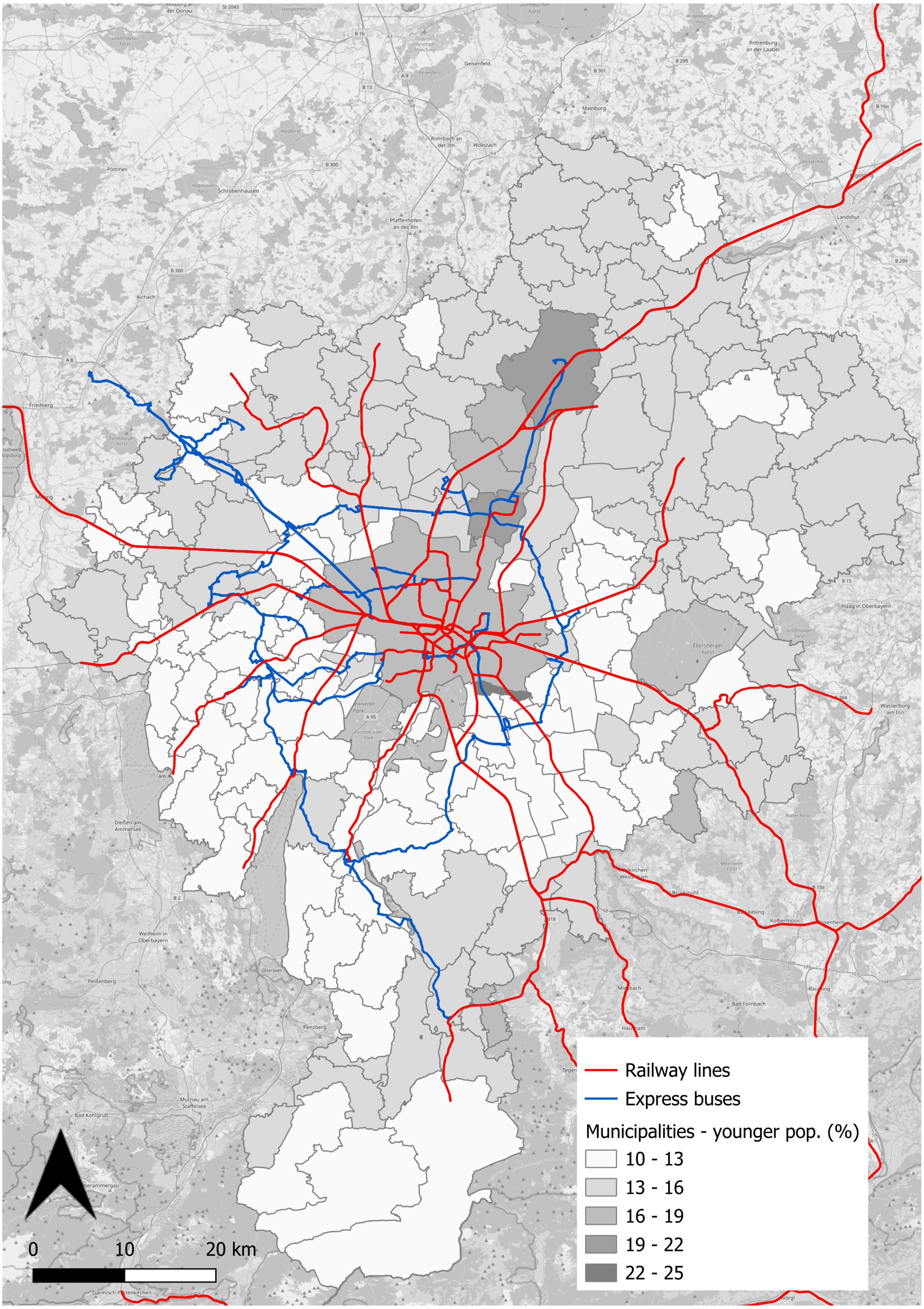

Figure 4.5 Distribution of younger population density (in percentages) of municipalities in the study area

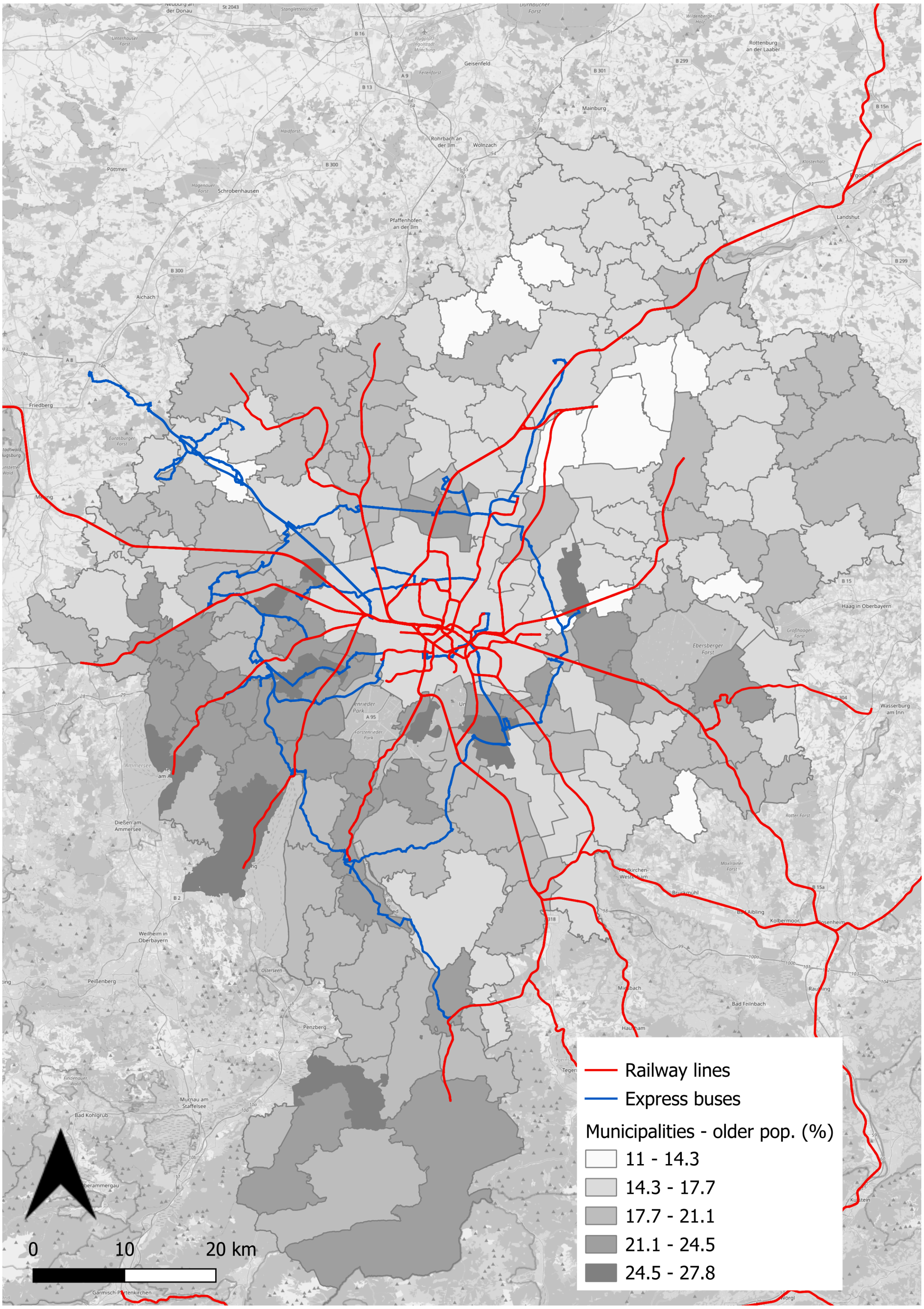

Figure 4.6 Distribution of older population density (in percentages) of municipalities in the study area

County	Total Population	Low-income	Unemployed	Disabled	Younger	Older
City of Munich	1,471,508	21.91%	2.08%	7.64%	17.16%	17.46%
Bad Tölz-Wolfratshausen	127,917	21.99%	1.15%	7.66%	13.07%	21.53%
Dachau	154,899	20.29%	1.06%	7.66%	13.64%	18.64%
Ebersberg	143,649	20.06%	1.01%	7.01%	13.3%	18.69%
Erding	138,182	19.89%	1.08%	7.09%	14.09%	17.15%
Freising	180,007	22.18%	1.24%	6.61%	16.16%	15.97%
Fürstenfeldbruck	219,311	20.51%	1.36%	7.93%	12.86%	21.67%
München (Landkreis)	350,473	20.25%	1.18%	7.17%	13.59%	20.49%
Starnberg	136,667	21.00%	1.17%	6.82%	12.08%	23.05%
Outlying municipalities[1]	30,442	20.21%	1.07%	6.33%	13.38%	18.32%
Total	2,953,055	21.34%	1.62%	7.44%	15.39%	18.58%

[1] Outlying municipalities include Geltendorf, Holzkirchen, Otterfing, and Valley, which are served by the S-Bahn but not in the above counties.

Table 4.2 Total population and percentages of underprivileged population segments in the inner suburban area by county

4.2 Application of the methodology

4.2.1 Categorization of municipalities

Due to the radial layout of Munich's rapid transit network, accessibility of municipalities, especially towards downtown Munich, could vary significantly depending on whether the location is directly served by rapid transit. Passengers from municipalities which do not have access to these services are often forced to take infrequent local buses to nearby areas as a feeder to the rapid transit network. Therefore, a distinction is made between municipalities which are served by rapid transit and otherwise to capture the effect of high accessibility as a result of direct service towards the city.

Figure 4.7 shows the distribution of rapid transit service areas, which generally follows the S-Bahn lines in a radial form. Out of the 179 suburban municipalities, rapid transit reaches 74 (41.34%) of them. This means over half of the municipalities are not served by rapid transit and thus less accessible. Note that while there exist municipalities beyond the S-Bahn area that are served by regional rail services out of Munich main station, with the exception of Moosburg a.d. Isar (Freising county) which has a near half-hourly service throughout the day, these regional services often run once every hour or less during the day, and the integration of such services into the MVV varies by route. Therefore, these outer municipalities are not considered to be served by radial lines in this study.

County	Municipalities served by rapid transit	Municipalities total
Bad Tölz-Wolfratshausen	2	21
Dachau	10	17
Ebersberg	7	21
Erding	3	26
Freising	5	24
Fürstenfeldbruck	11	23
München	22	29
Starnberg	10	14
Total	70	175

Table 4.3 Number of suburban municipalities served by rapid transit in each county (The four outlying municipalities in Miesbach and Landsberg counties, and the City of Munich are excluded in the table)

Table 4.3 and Figure 4.7 both show the coverage of rapid transit in the Munich suburban area. The 2017 MiD survey (MVV, 2020) reported that residents in Fürstenfeldbruck, München, and Starnberg counties generally perceive public transit services positively, while other counties have a more negative bias towards transit. This could be reflected from the situation where out of the 74 suburban municipalities served by rapid transit, over half of them (43) are located in the three well-received counties. Rapid transit provides regular frequent service between the suburbs and downtown Munich, which is a determinant factor when considering temporal accessibility, and thus the existence of such connections could also affect passenger perceptions towards the transit system. This distinction is also reflected in Equation 3.5 for the regression analysis, where a dummy variable regarding rapid transit service is included.

4.2.2 Geospatial analysis

The computation of population centroids for municipalities requires accurate population distribution. The 2011 German national census data (Statistische Ämter des Bundes und der Länder, 2013), which is aggregated to 100m$\times$100m grid cells, was used for this purpose.

4.2.3 Calculation of accessibility and decay index

To calculate accessibility ratios using Equation 3.1, destinations are weighted using O-D travel demand. The travel demand matrix is obtained using the 2011 synthetic travel demand data set for the Munich Metropolitan Region by Moeckel et al. (2020). This data set was calibrated against results from the MiD survey and traffic counts, and thus, whereas errors might occur at the coordinate level, this data set could more or less accurately reflect the actual demand on the municipality level in general.

Travel time costs are computed using the Germany-wide GTFS data set provided by DELFI. The advantage of using GTFS data is that planned construction works and their resulting timetable changes are reflected into the feed. This means R5R could extract the appropriate trips and calculate the shortest path for each selected scenario without first editing the GTFS feed manually.

However, despite allowing a travel time budget of 4 hours (240 minutes), trip durations for some O-D combinations could not be calculated, possibly due to long trip durations, a lack of adequate public transit services in the concerned municipalities, or internal bugs within R5R. For the sake of this study, these O-D pairs are assumed to have an infinite travel time cost to account for the low ease to complete such trips by public transport.

To compare the accessibility indices during disruptions, the normal service scenario **C0**, which was on a typical November weekend, was compared against a construction work scenario **C1**. This happened on Saturday, 21 October 2023. The S-Bahn trunk line between Pasing and Ostbahnhof is completely closed and replaced by buses throughout the weekend for construction work, which leads to trains rerouting or short-turning. This means passengers cannot use the S-Bahn to access the city center directly, and due to the concentration of transfer opportunities with other modes at the city center, accessibility is further hindered. For both scenarios, accessibility ratios AR_i are computed on the municipality and network extents to assess the network performance under these disruption scenarios, and the corresponding population-weighted decay index $I_{i,k}$ could then be obtained using population composition data.

By this step in which values of $I_{i,k}$ have been obtained, initial insights and conclusions regarding population segments more vulnerable to transit service disruptions in each area could be drawn. Nonetheless, the linear regression analysis is performed to infer the effect towards AR_i by each population segment. Models will be developed for each of the counties and the entire S-Bahn service area to analyze which population segments are more vulnerable to transit disruptions and the lack of resilience in the network.

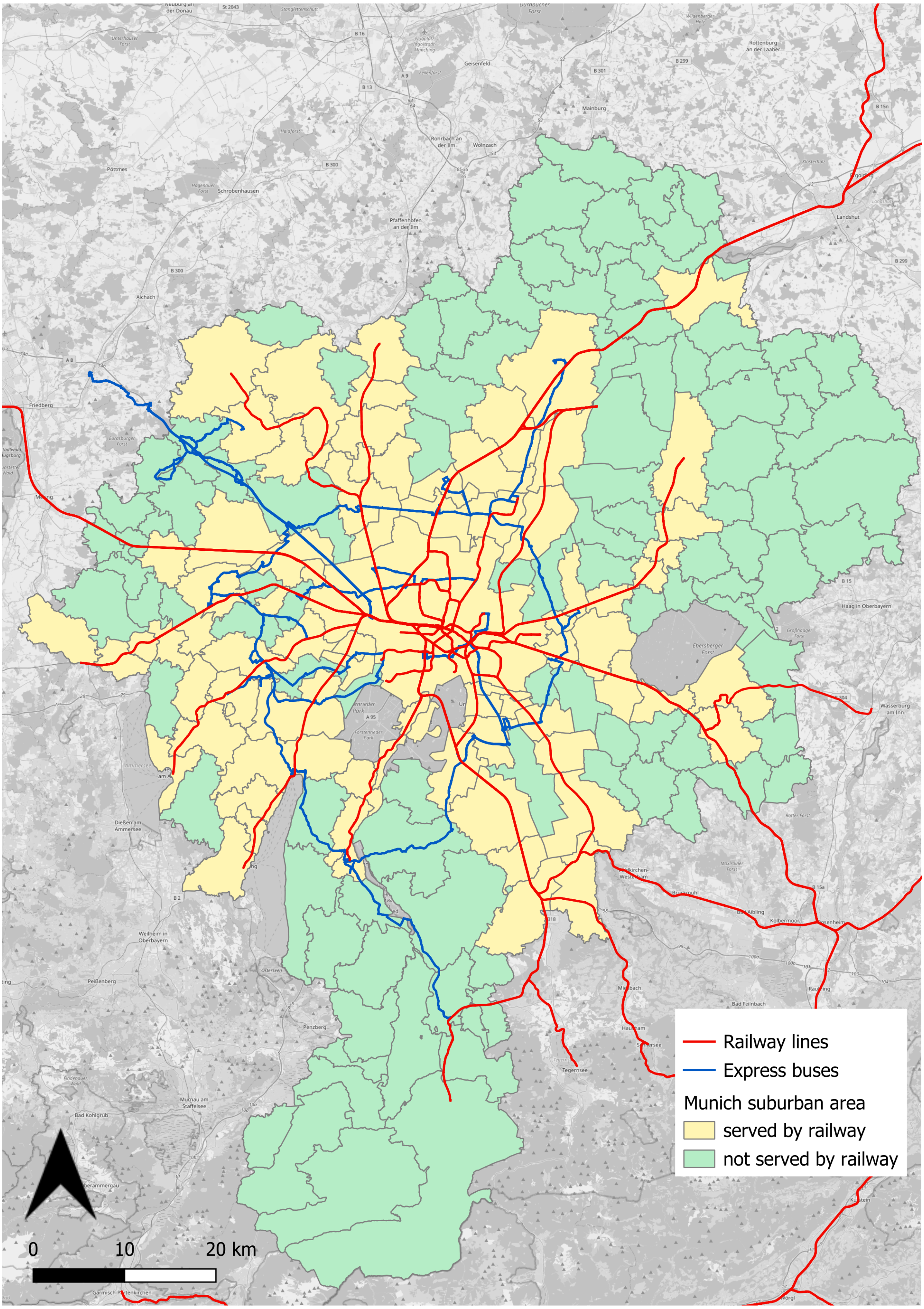

Figure 4.7 Map of the Munich inner suburban area, highlighting the rapid transit service area (own work, using data from OpenStreetMap contributors (2023))

5 Results

5.1 Accessibility decay analysis

Out of the 180 municipalities within the Munich inner suburban area, accessibility ratios AR_i were obtained for 145 municipalities using Equation 3.1. It was unable to calculate the other 14 municipalities due to them being excluded from the synthetic travel demand, and calculations for AR_i for the remaining 21 municipalities failed as R5R was unable to compute O-D travel time costs for these municipalities.

Although AR_i should be greater than 1 due to the longer trip duration and detour, the shortest path algorithm used by R5R has resulted in some AR_i values lower than 1. Table 5.1 shows the range of AR_i which clearly shows about a quarter of municipalities have AR_i values lower than 1.

Statistical indicator	AR_i
Minimum	0.84
1st-quartile	1.00
Median	1.00
Mean	1.02
3rd-quartile	1.04
Maximum	1.30
Standard deviation	0.05
AR_{global}	1.02

Table 5.1 Statistical indicators for AR_i and global AR value

As shown in Table 5.1, despite having a monocentric radial public transport network and a clear modal hierarchy, municipalities in the Munich inner suburban area experience accessibility decay to a low extent, which suggests a high robustness in the transit network. Moreover, Figure 5.1 depicts the distribution of AR_i values over the study area, and has shown that the existence of S-Bahn services does not correlate with the value of AR_i. In fact, municipalities along S-Bahn corridors often perform worse in AR_i values when compared to those without without S-Bahn connections. This could be due to the S-Bahn being directly connected to central Munich, and thus when the trunk line is blocked, accessibility could deteriorate severely. This could be reflected when the AR_{global} values are computed for municipalities with radial rail connections and those without separately. Table 5.2 shows the difference in AR_{global} values depending on the existence of radial connections.

Municipality characteristics	AR_{global}
With radial line connection	1.0175
Without radial line connection	1.0170

Table 5.2 AR_{global} values for municipalities with and without radial rail line connections

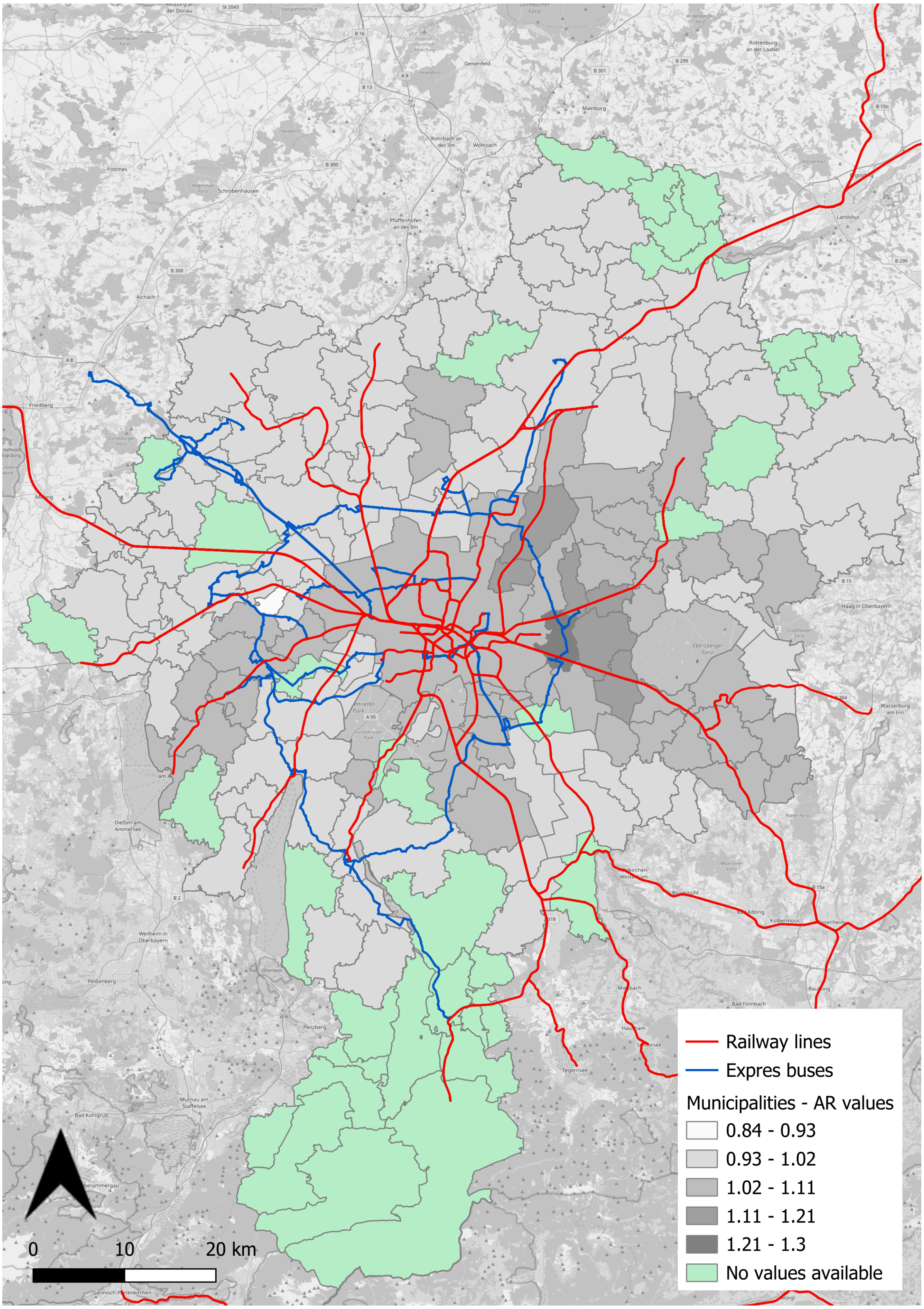

Figure 5.1 Map of accessibility ratio AR_i distribution over the study area

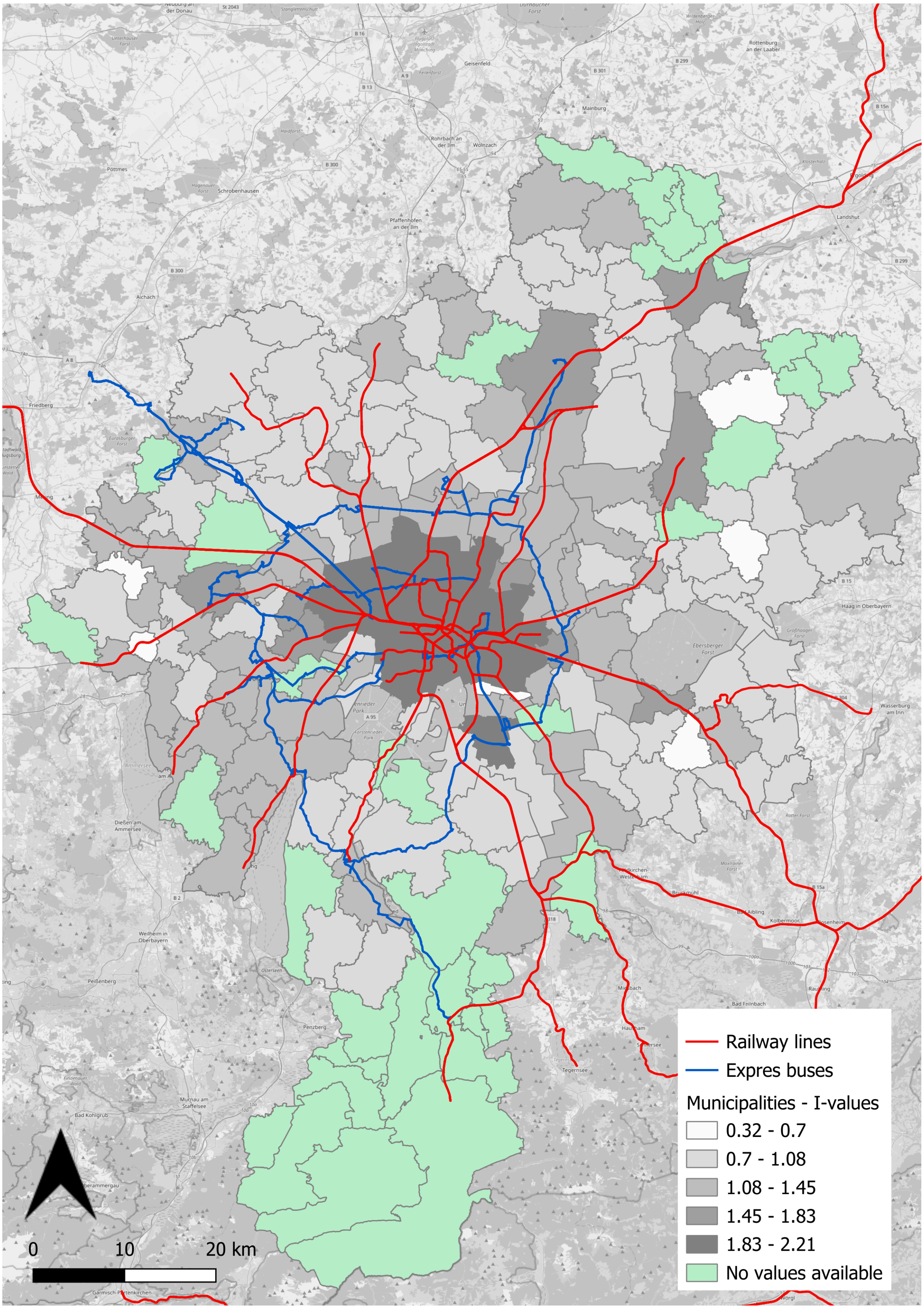

Figure 5.2 Map of weighted accessibility decay index I_i distribution over the study area with respect to the unemployed population

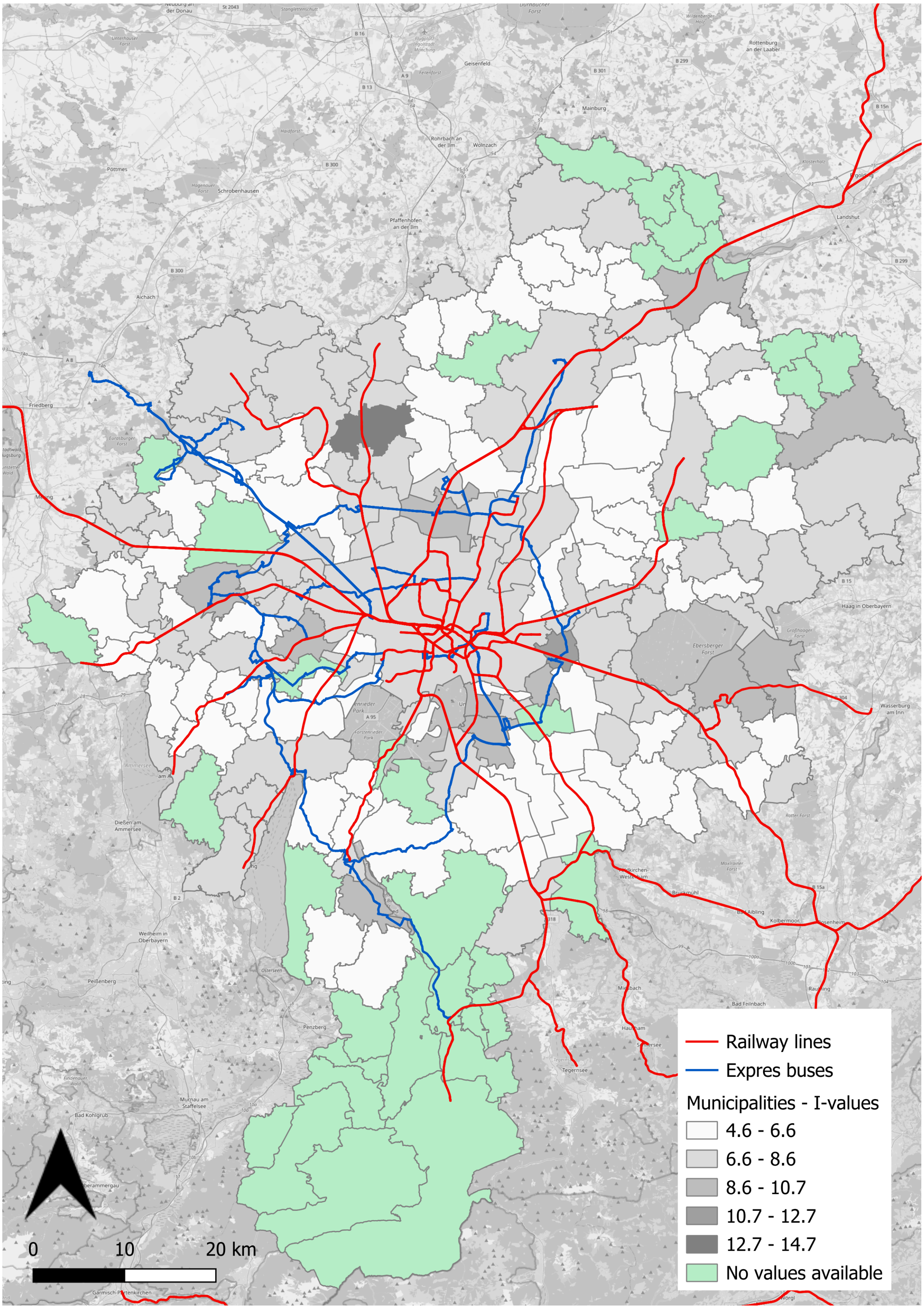

Figure 5.3 Map of weighted accessibility decay index I_i distribution over the study area with respect to the disabled population

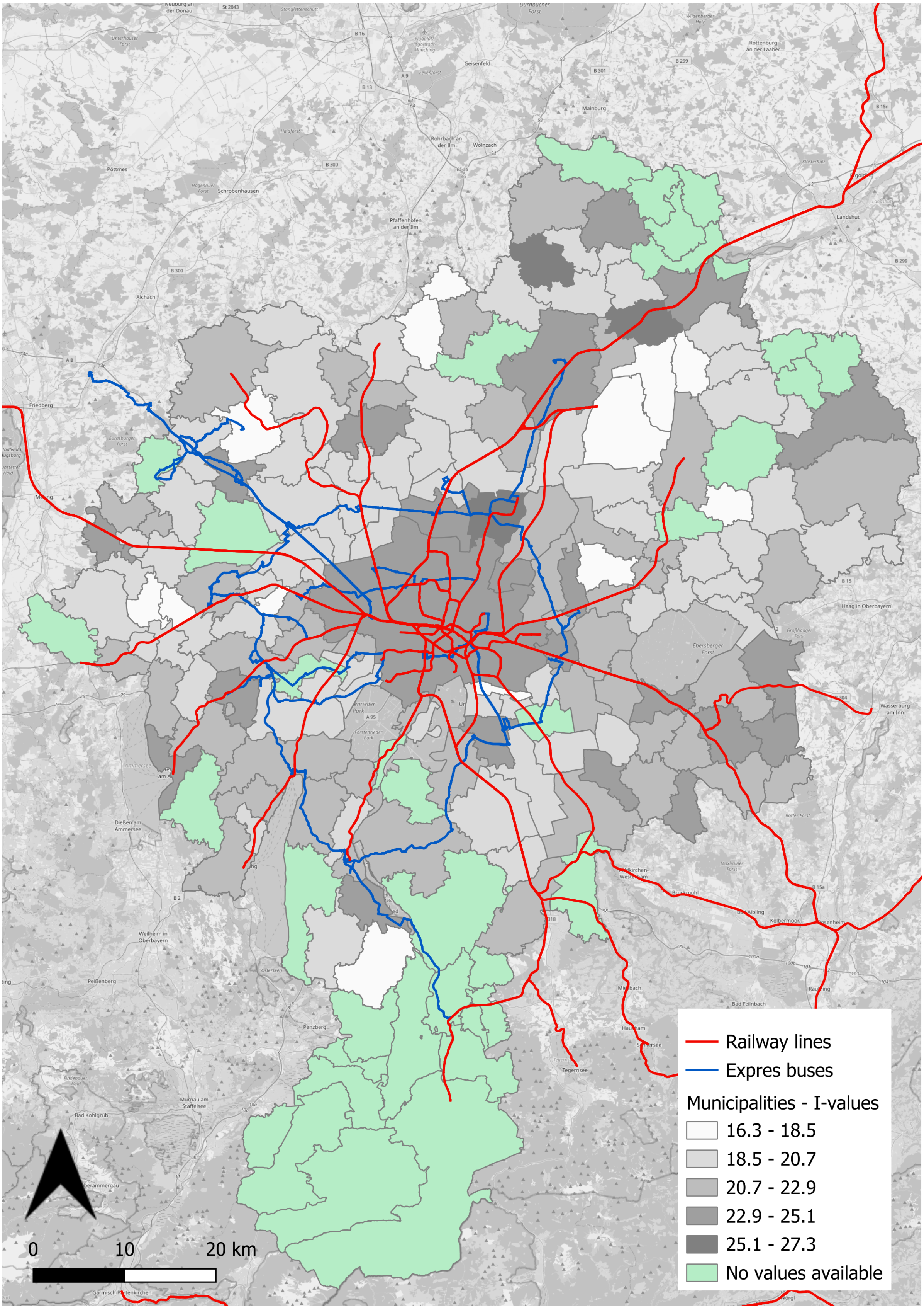

Figure 5.4 Map of weighted accessibility decay index I_i distribution over the study area with respect to the low-income population

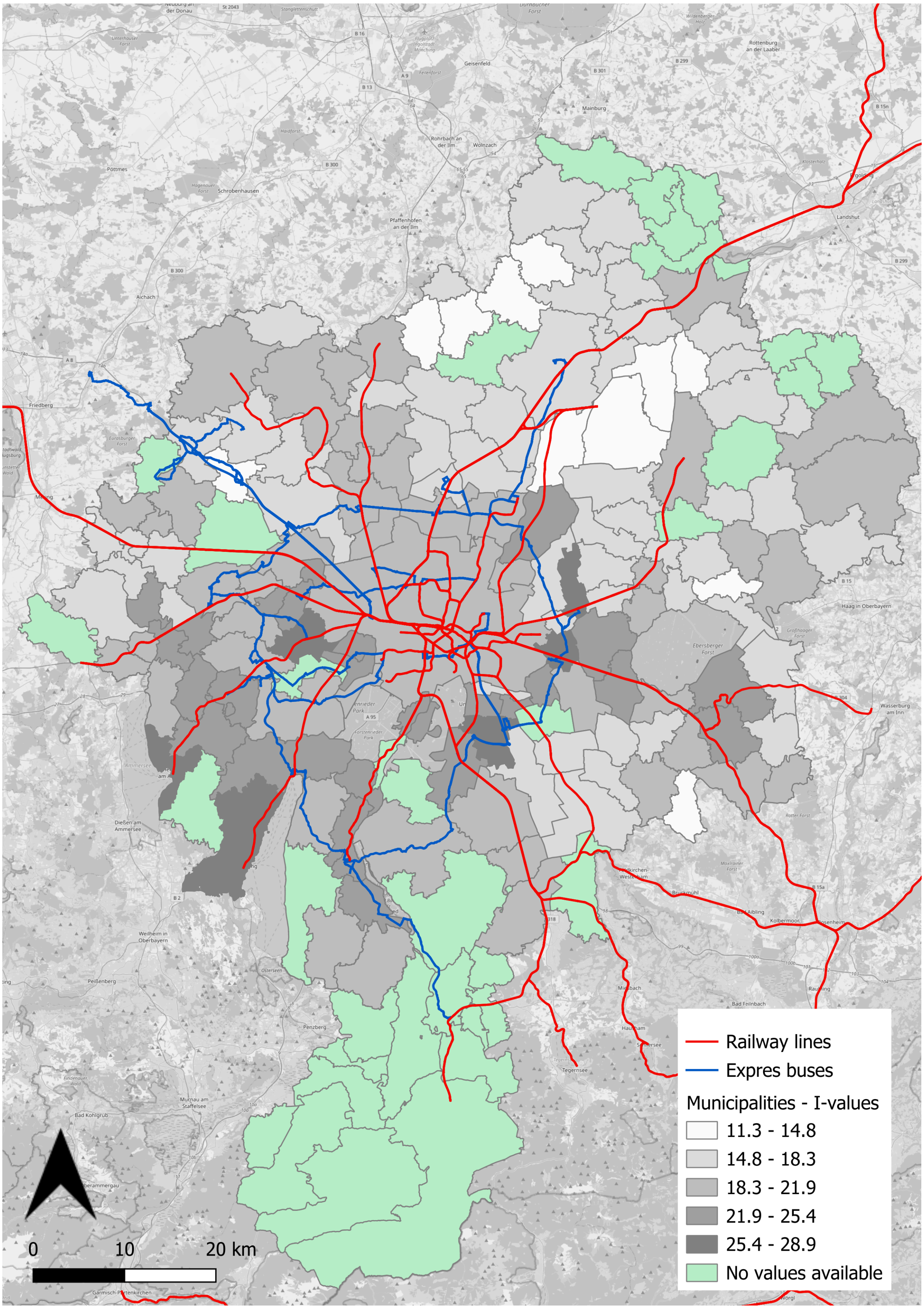

Figure 5.5 Map of weighted accessibility decay index I_i distribution over the study area with respect to the older population

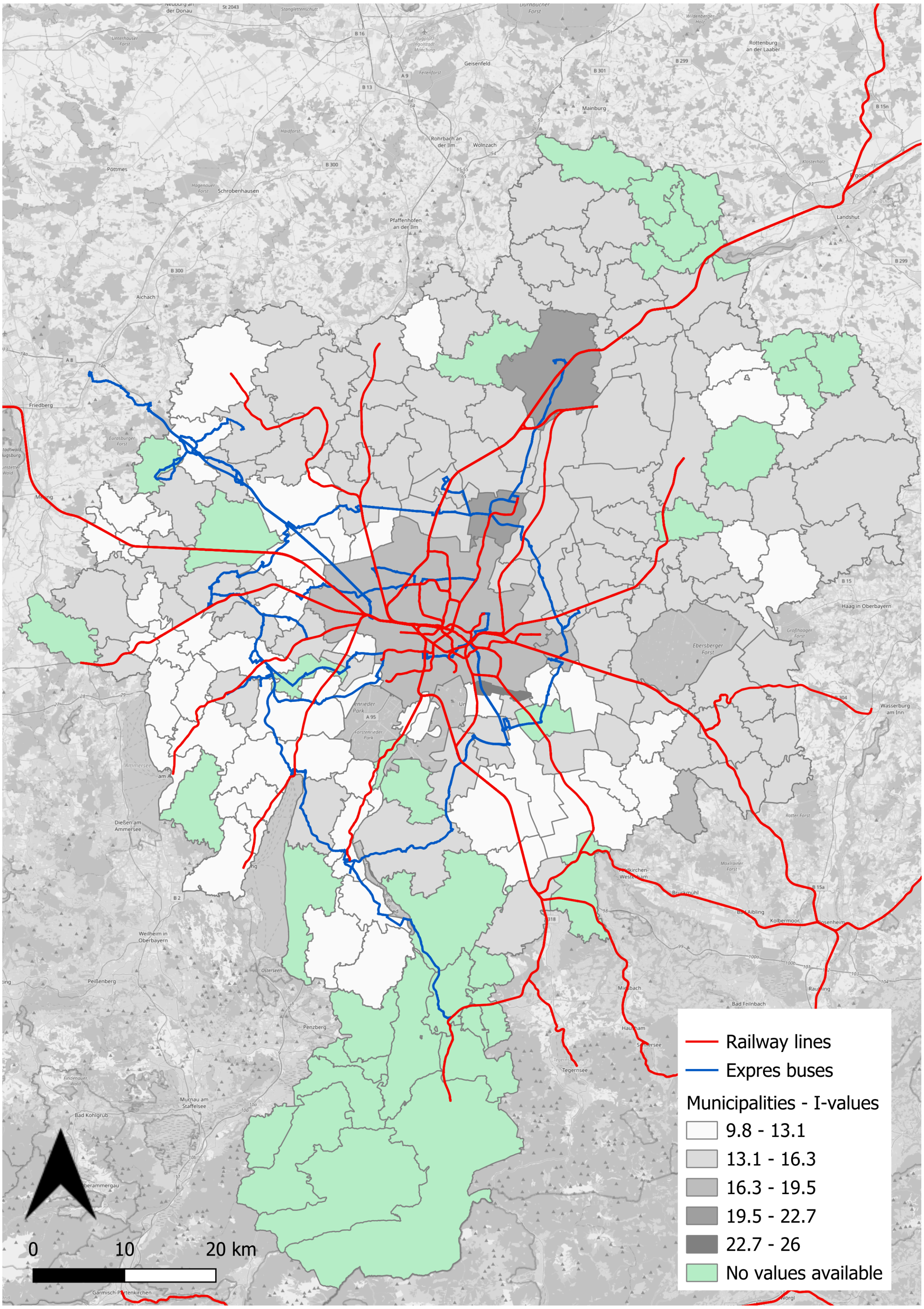

Figure 5.6 Map of weighted accessibility decay index I_i distribution over the study area with respect to the young population

5.2 Accounting for target population segments

Weighted accessibility decay indices $I_{i,k}$ for each municipality and target population group were obtained using Equation 3.3. The ranges, mean, and standard deviation values of the indices for each population segment are summarized in Table 5.3:

Population group	Minimum	Mean	Maximum	Standard deviation
Unemployed	0.32	1.08	2.21	0.27
Disabled	4.56	6.94	14.75	1.35
Low-income	16.28	20.86	27.26	1.96
Older	11.28	19.18	28.92	3.49
Younger	9.84	13.75	25.98	1.92

Table 5.3 Ranges, mean and standard deviation values for weighted accessibility decay indices $I_{i,k}$

As seen from Tables 4.2 and 5.3, the higher proportions of old population and low-income taxpayers influence the higher $I_{i,k}$ values for these groups, while the young population also plays a prominent role, albeit less prominent than the previously mentioned groups. While the mean values could provide a rough insight on the vulnerability extent the population segments are subject to transit service disruptions, it must be noted that these values are computed based on population composition, and thus while this holds true in the Munich S-Bahn area, the same could not be claimed as true for any study areas.

Regarding the distribution of $I_{i,k}$ values over the study area, Figures 5.2 to 5.6 show the distribution of $I_{i,k}$ values across the study area. These distributions depict reverse situations from the case of AR_i analysis. The City of Munich performed much worse in terms of I_i in comparison to AR_i due to the higher proportions of the underprivileged population residing within the City of Munich when compared to the suburban municipalities.

5.3 Regression analysis

To examine the effect of population compositions towards public transport service resilience, a multivariate linear regression model was generated using R according to Equation 3.5.

5.3.1 Multi-colinearity check

Figure 5.7 shows the correlation plot between predictors. It could be observed that the predictor of older population composition is more prone to multi-colinearity as it has correlation values of 0.47 against the categorical variable of radial lines and the disabled population composition predictor. However, from Table 5.4, the variance influence factor (VIF) values for all predictors do not exceed the threshold of 2.5, which means multi-colinearity is not a serious issue in this model.

Radial line	Unemployed	Disabled	Low-income	Older	Younger
1.507	1.377	1.546	1.306	2.147	1.490

Table 5.4 VIF values for the predictors

5.3.2 Summary of model

From Table 5.5, the coefficients for compositions of unemployed and disabled populations are positive, with the one for unemployed population being more positive. This implies higher concentrations of these

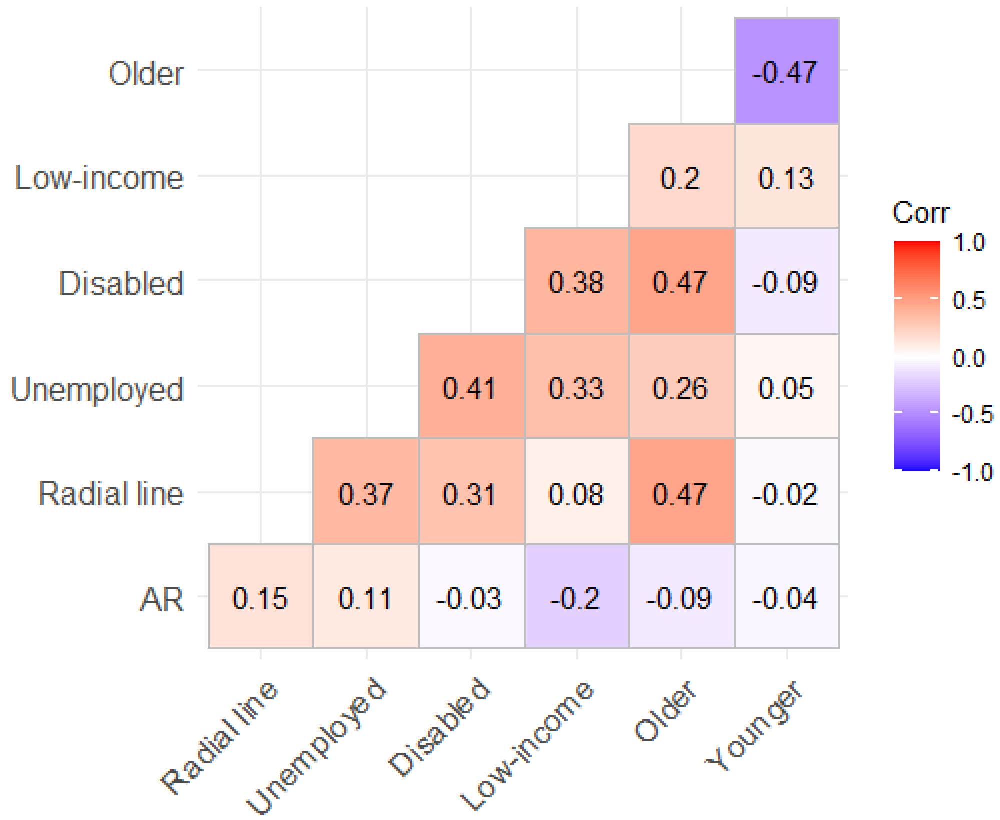

Figure 5.7 Correlation plot between predictors

two population groups would negatively affect the network resilience as they are more vulnerable to transit service disruptions. For low-income, older and younger population groups, the slightly negative coefficients mean that they are less vulnerable to transit service disruptions, as increases in population composition of these groups decrease the value of AR_i. The positive coefficient for the radial line predictor also proves that a direct connection to central Munich would make the municipality more vulnerable to disruptions.

From the p-values, it could be observed that the disabled and younger population groups are statistically insignificant due to their higher p-values. The p-value for unemployed workers is also less significant than the remaining two groups, even though it falls under the 0.01 significance threshold. This means that older and low-income population influence the model more.

5.3.3 Hypothesis testing

As stated in Table 5.5, the compositions of unemployed, low-income and older populations statistically significantly influence the value of AR, especially in the case of unemployed residents where higher percentages of such residents would increase the value of AR_i. While the coefficients for the standardized population compositions are low, the results still run contrary to the null hypothesis **H0**, in that all population compositions are not significant in affecting network resilience through the AR value. Hence, the thesis rejects **H0** and accepts the alternative hypothesis **H1**.

	Dependent variable:
	AR_i
Radial line	0.023^{**}
	p = 0.026
Unemployed	3.365^{*}
	p = 0.091
Disabled	0.104
	p = 0.798
Low-income	-0.570^{**}
	p = 0.032
Older	-0.438^{**}
	p = 0.019
Younger	-0.429
	p = 0.141
Constant	1.226^{***}
	p < 0.001
Observations	145
R^2	0.119
Adjusted R^2	0.081
Residual Std. Error	0.050 (df = 138)
F Statistic	3.105^{***} (df = 6; 138)
Note:	$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 5.5 Results of linear regression model

6 Discussions

6.1 Discussions on the methodology

6.1.1 Accessibility decay indicators

The methodology of this paper is based on the one used by Chang (2003) and Chang and Nojima (2001), namely on using an accessibility ratio to measure the decay in accessibility. This ultimately traces back to the concept of circuity as defined in Equation 2.4 by Barthélemy (2011), in that the indicators are measuring the ratios between the shortest path and the actual path taken. As disruptions or construction works occur, it would be necessary to take detours to complete the trip compared to the optimal path during normal service. This creates an opportunity to analyze the change in accessibility. As Crucitti et al. (2006) defined in Equation 2.5, averaging circuity values for a node could generate a network-based accessibility index for the concerned node that reflects the relative ease to access the node. The AR_i could therefore be seen as a variation of this iteration.

Referring back to the fundamental definition of accessibility in Equation 2.1 by Hansen (1959), accessibility could be defined as the potential of interaction opportunities while considering spatial separation through travel cost. The change or decay in accessibility as a result of circuitous trips, either due to the transit network layout itself when compared to automobile trips, or because of disruptions and resulting line closures that force passengers to use alternative paths to complete their trips, is a result from the fact that less destinations could be accessed within the same cost budget (Huang & Levinson, 2015).

The demand-weighted accessibility ratio AR_i, based on the one developed by Chang (2003) and Chang and Nojima (2001), reflects the detour factor for each node as accessibility decreases through the closure or destruction of network links. Comparing to the mentioned studies, which measures the accessibility performance simply on an infrastructure basis and takes distances as travel costs, this study incorporates more realistic aspects of public transit trips, such as fixed-route networks and transfers through the use of GTFS data and computations using the R5 algorithm. It is also calculated based on travel time, one of the major cost determinants for public transit users. This allows transit accessibility decay to be reflected more realistically from the perspective of riders. However, as mentioned further below, this approach should be used with caution due to shortcomings of GTFS data, especially as conventional GTFS feeds are static feeds that contain scheduled data and do not reflect real-time operational deviations or unplanned disruptions.

6.1.2 Accounting for underprivileged or transit-dependent population segments

There has been a gap in research in the impact on underprivileged or transit-dependent population due to the lack of network resilience. This thesis therefore developed a population-weighted accessibility decay index $I_{i,k}$ based on AR_i in order to take such population segments into consideration. As this is basically a weighted AR_i by the proportion of each population segment considered, it can consider the impacts towards different population groups separately, thus cater the requirements of developing a transport equity indicator as mentioned by Martens et al. (2019).

As Kenyon et al. (2002) explained, there exist various factors that result in mobility-related social exclusion, itself being the result of reduced accessibility or insufficient mobility to undertake social functions. High $I_{i,k}$ and AR_i values could be interpreted as a potential warning indicator to social exclusion for transit-reliant passengers since accessibility is severely deteriorated during disruptions, especially if rapid transit acts as a lifeline to social activities for the users. Whereas neither AR_i nor $I_{i,k}$ captures the perceived accessibility of users directly, especially because perceived accessibility involves more subjective assessments such as satisfaction and comfort (Lättman et al., 2016; Lättman et al., 2018), these values could still indirectly reflect whether users would travel during disruptions, especially if the indicator values suggest high circuity ratios and thus imply more transfers, which can be perceived as a disutility (Cascajo et al., 2017) and thus inhibit residents from partaking in social functions due to the impedance to travel should the circuity and the resulting travel disutility increases. As Kenyon et al. (2002) warned, mobility-related social exclusion, such as due to the inability to access public transit, often reinforces social exclusion in other dimensions such as economic, political, environmental, or cultural aspects. This ultimately results in increasing deprivation among underprivileged social groups and the fragmentation of social structures (Bocarejo S. & Oviedo H., 2012).

Whereas this thesis used a generalized approach which assessed accessibility decay between municipalities, the same methodology could be extended to cater for the needs of specific demographics, such as including points of interests specific to the population groups concerned like hospitals, care homes, or universities as population group-specific destinations to further investigate the impact towards the population segments during transit service disruptions. Recalling the theories by Delbosc and Currie (2011) and Litman (2002), public transport could operate under either the "mass transit" or the "social transit" paradigms depending on which equity approach (horizontal or vertical) is considered. Vertically equitable transportation systems should aim to achieve social justice by considering impact distribution among user segments thoroughly, such as those incurred towards passengers during disruptions. As a rule of thumb, when designing policies to achieve social equity, resources should be distributed such that underprivileged or disadvantaged users are appropriately compensated when inequitable situations occur, and not simply distributing the resources equally across all demographics as in a horizontal equitable system. Therefore, under the "social transit" paradigm, it is of utmost priority to consider how transit-reliant passengers are affected during disruptions when planning contingency procedures, and therefore allocate resources to better compensate these users.

The structure of AR_i as the ratios of sums of weighted travel costs adds a layer of versatility to calculations. While this study takes AR_i as the accessibility ratio to all municipalities within the study area, each analysis zone (such as a county, municipality or city borough) may have several AR_i values to suit the research demand when multiple sets of points of interest are studied. This can be achieved simply by manipulating the set of O-D pairs that are considered in the AR_i. While not being tested in this thesis, the potential of tailoring AR_i values to the needs of different population segments could help planners to comprehend how accessibility would be impacted onto different user groups.

6.2 Discussions on the results

6.2.1 Accessibility decay analysis

The distribution of AR_i values over the study area in Figure 5.1 shows an interesting pattern. Municipalities along S-Bahn corridors often perform worse than those away from S-Bahn corridors, having greater AR_i values in this case. A possible explanation for this phenomenon is the direct connection to central Munich with the S-Bahn for those municipalities, and as Munich's public transit network is of a radial structure with a strong hierarchy, the disruption of an important link such as the S-Bahn would cause network connectivity to severely deteriorate by disconnecting network segments from the rest. The radial network structure in Munich poses additional challenges where there are no circumferential or tangential rail connections between radial corridors, which means feasible alternative routes are often unavailable. Using buses to connect to other lines would prolong the trip excessively and could render the alternative path infeasible. As Xu et al. (2015) explained, a lack of travel alternatives as a result of poor connectivity could be problematic during disruptions, as this fails to meet the travel alternative diversity criteria on having high resilience on a public transit network. Recommendations to overcome the topological disadvantages of radial networks, such as including loop lines that serve as tangential connections outside the core (Laporte et al., 1997; Saidi et al., 2016), also double as measures to improve network resilience by providing users a feasible alternative route to bypass the blocked paths.

Another effect on accessibility is the necessity to take detours, which involves prolonged trip durations and additional transfers, and thus contribute to a drop in travel utility. Referring to Cascajo et al. (2017), transfers are poorly perceived by passengers, even to a point where circuitous one-seat rides are preferred over direct trips with transfers. With the disruption case in mind, not only do passengers need to undergo extra transfers, but it is very often the case where the overall trip duration is lengthened. Ultimately, the increased travel duration, number of transfers, as well as other factors such as decreased comfort due to insufficient capacity on the alternative routes, all contribute to the disutility of transit users and in turn lower accessibility values during disruptions.

Given a strong hierarchical structure in Munich's suburban transit network, it is of no doubt that a direct S-Bahn connection plays a prominent role on whether a municipality is highly accessible to central Munich and by extension locations along other rail corridors. However, AR_{global} values for these locations have seen that such structure is not resilient enough, and they could even underperform municipalities without S-Bahn connections. While passengers in municipalities without S-Bahn connections need to use buses as feeder services, there also exist municipalities where local or express bus services connect multiple rail corridors and thus contribute to the higher resilience through lower AR_i values.

6.2.2 Accounting for underprivileged population

Comparing Figure 5.1 with Figures 5.2 to 5.6, the City of Munich performed worse in terms of $I_{i,k}$ values when compared to AR_i analysis. This could be attributed to the higher concentrations of underprivileged population in the City than in the suburbs. As $I_{i,k}$ weighs AR_i by the population composition, higher proportions of the concerned population segments contribute to higher $I_{i,k}$ values.

As shown in Figures 4.2 to 4.6, the City of Munich has some of the highest proportions of unemployed and low-income population across the study area. A plausible reason could be the concentration of job opportunities in the City, and such unemployed people are more likely to reside within the City to attempt to search for jobs more easily, while low-income workers would try to minimize their expenses on public transit by residing in the city limits. As the City of Munich itself forms a single central flat fare zone in the MVV network, low-income workers might tend to reside towards the fringe areas within the city instead of moving out towards the suburbs, which are situated in separate fare zones that incur additional trip costs.

6.2.3 Regression analysis

The results of the regression model as summarized in Table 5.5 showed some interesting patterns. Higher proportions of unemployed and disabled populations contribute to greater AR_i values, while the other three groups contribute to smaller AR_i values. This means disabled and unemployed people are more vulnerable to disruptions. While it is intuitive that disabled people are more vulnerable to disruptions due to their need to access healthcare regularly, the reason behind the opposing impacts towards AR_i by unemployed and low-income people, and thus their vulnerability towards transit disruptions, is understudied. Sanchez et al. (2004) summarized theories suggesting how these users are disadvantaged. While there exist theories suggesting spatial disadvantages due to the inaccessibility to automobiles, others contradict this and suggest the reliance on unreliable, meandering transit services as a reason. However, one thing that can be sure from the model is that proportions of both population groups are significant towards the AR_i value, given their high reliance on transit. For younger residents, the age group considered in this study (18 to 25) corresponds to the age group for typical university students. Given the presence of large research campuses in Garching and Freising, it is of a high probability that students based in these campuses would reside within their respective municipalities to minimize their commute costs, thus contributing to higher population concentrations and travel demand for these locations.

The explanation for the negative coefficient for the older population, however, is slightly more complex. Referring to Figure 5.7, the predictor for the older population is more prone to multi-colinearity due to a high correlation value against disabled population proportions. The predictor also possesses the greatest VIF value among all independent variables. This could be attributed to the high probability for older people to be disabled the same time. Research such as Berg et al. (2014), Burnett and Lucas (2010), and Mollenkopf et al. (2011) discovered changing mobility behaviors during the transition into retirement, such as overall reduced travel activities due to reduced physical ability. This overall reduced travel behavior means older users might in general use less transit, and thus explains the negative coefficient in the model, as this lower demand could mean they are less vulnerable towards disruptions.

6.3 Limitations

A shortcoming of using standard GTFS data is the inability to capture disruptions due to unpredictable incidents, since standard GTFS data only contains scheduled data, while real-time data is captured in separate GTFS Realtime (GTFS-RT) feeds. This created a challenge in the thesis, as with conventional GTFS feeds, only construction work disruptions that are already reflected in the schedules could be used to replicate the disruption scenario. During incidents or emergencies, operators are more keen on keeping the system in operation and would be more flexible on dispatching services, which is completely contrasting to a planned closure during constructions.

The AR_i and $I_{i,k}$ values, while being straightforward to calculate, do have their own shortcomings. In this study, a synthetic travel demand is used to calculate the AR_i values and then multiplied by the population compositions to obtain the accessibility decay index for each population segment. However, travel demand within a particular population segment need not be proportional to the overall travel demand, especially when the O-D pairs consider points of interest and not generic spatial units. A remedy to this could be to directly inquire the travel demand for the population group and use this to calculate the AR, in which the value would reflect the accessibility decay for the O-D pair for the particular user group. Such demographic-specific travel demand, however, could be challenging to obtain, let alone collecting, and thus the approach considered in this thesis could be a suitable alternative.

While this thesis mainly investigates the network aspects of accessibility by analyzing network connectivity in general, accessibility itself is a multifaceted study area which also includes spatial, temporal and personal aspects (Geurs & Ritsema van Eck, 2001). Therefore, achieving a socially inclusive public transport system requires thorough understanding of the target population segments, such as the quantity of travel demand, frequently traveled time periods, or their own personal needs towards public transit. Ultimately, it is essential to incorporate both objective and perceived accessibility analyses to fully comprehend the needs of transit users. As low perceived accessibility could imply low satisfaction towards the transportation system, given the intertwined nature between objective and perceived accessibilities, there could be additional potential demand that is being neglected. Such neglected potential demand is often the result of potential users not traveling at all due to their perceptions to the transit network, which could be realized should service be improved, such as improved accessibility.

As shown in Table 5.1, about a quarter of municipalities had AR_i values less than 1, implying that accessibility during a trunk line closure would be better than during normal service. A possible explanation for this counterintuitive result could be due to the algorithms that R5R used to compute travel times. One problem is that the travel time matrix for case **C1** sometimes returns faster travel times than for case **C0**. The R5 routing algorithm is based on the Round-Based Public Transit Optimized Router (RAPTOR) routing algorithm (Conway et al., 2017) to compute the optimal public transit trip duration. As Delling et al. (2015)

pointed out, travel time is not the sole determinant for computing optimal paths on public transit networks, and other factors like transfers or monetary costs often place as much importance as travel time. Thus the RAPTOR algorithm aims not only to minimize the travel time, but also the number of transfers made on a trip. This might result in the routing algorithm prioritizing slower one-seat rides over faster trip combinations with transfers in case **C0**, especially when the S-Bahn is concerned. A second reason to this could be simply due to different operating timetables during case **C1**, especially when trains are routed onto the long-distance tracks and therefore skip the inner-city S-Bahn stops, which contribute to the faster trip durations. Such counterintuitively faster travel times, combined with the demand weighting, eventually result in unrealistic AR_i values of less than 1.

Besides, this study uses municipalities as the spatial unit of study, which means only inter-municipality travel is actually considered in the study. It should be noted that this limitation is caused by the demographic data that can be obtained from official sources, which are accurate to the municipality level. Census data, while having the advantage of sorting data into 100$\times$100 meter grid cells, do not provide detailed demographic data within each grid cell out of privacy reasons. A finer distribution of the population considered in this study, such as assigning population to the nearest public transit stop, was therefore not possible. This means intra-municipality trips could not be evaluated since they would be essentially having the same origin and destination points in the model. Whereas a general resilience analysis using total population data could be possible using the same methodology with higher accuracy, data availability means it is not possible to improve the accuracy of this study.

7 Conclusions

7.1 Findings of the thesis

This study has developed a straightforward methodology to measure the impact of transit service disruption on underprivileged, transit-reliant population, and by extension the effects of a lack of resilience on the public transit network to these users, in order to address the existing research gap on the intersectionality between network resilience and transit equity. As transport planning moves on to a more equitable and sustainable paradigm, it is important to consider the impacts towards different passenger groups and to design policies based on their needs. Accessibility is considered one of the important performance indicators for transportation systems, such as evaluating impacts of disruptions towards passengers, where a decay factor might be useful. The methodology proposed in this paper has the advantage of being compatible with existing data such as population compositions, travel demand and travel times, and could be readily adapted to GIS and coding environments for computation. As Chang and Nojima (2001) mentioned, while sophisticated models could be used to achieve the same purpose of calculating accessibility decay, especially in metropolitan regions, these models themselves are already data-intensive and are often tailored for one region, and adding the population composition factor would further complicate the model. These simple, generic methods therefore, have the advantage of rapid calculations and the ability to enable inter-regional analysis.

The linear regression model acts as an extension to the geospatial accessibility decay analysis, in that the regression equation provides a generic overview of how vulnerable are the concerned demographics towards disruptions through assessing the relationships between population compositions and AR_i. The case study of the Munich suburban area found that disabled and unemployed people are more vulnerable to disruptions and the lack of resilience in transit networks, echoing findings of previous research. While the regression model does vary by study area, it does have the advantage of allowing planners and researchers to inquire the demographics that are more vulnerable to disruptions, and assess the impacts towards accessibility should there be changes to population compositions.

As transport planning starts to emphasize more on social equity aspects, it is essential for researchers and planners to understand the causes and effects of inequity in the current transport planning paradigm, and thus identify solutions to remedy this inequity situation. Inequity indicators, such as those developed in this paper, could be useful in identifying deficiencies in accessibility and the impacts on individual population segments. By quantifying the performance in accessibility decay during disruptions, the indicators allow decision-makers to have objective values on deciding the permissible threshold of AR_i or $I_{i,k}$ before interventions should be taken. As the ultimate goal of public transit should be to serve the entire population, thorough consideration across all population segments is needed when setting policies or emergency plans, such that the inconveniences caused to passengers are appropriately compensated.

7.2 Recommendations to stakeholders and future research

With real-time transit data becoming available through GTFS-RT feeds, it is expected that future research could attempt to combine the methodology proposed in this thesis with dynamic GTFS-RT feeds that reflect real-life variations and unplanned disruptions. As stated above, operators are more keen on keeping the system in operation and thus are more flexible when developing emergency plans, which is different from planned constructions where timetables could be planned in advance. As accessibility research using GTFS-RT data such as L. Liu et al. (2023, 2024) starts to evolve, it would be interesting to see how real-time data could assist researchers in identifying deficiencies in transit service, especially on the equity aspect. Such emerging research have been applying real-time data into accessibility analysis to capture the effects of actual operational deviations or disruptions, and such data could be valuable in assessing transit system resilience. The next step could be to further develop these methods to account for transit-dependent population segments and assess the extent of vulnerability towards such service disruptions.

An application potential is to incorporate demographic-specific points of interest within the study area to assess accessibility decay more accurately. The methodology used in this study is compatible with OpenStreetMap data and can be easily adapted to GIS environments, which are commonly used in research and planning contexts and are readily available, and is thus flexible in terms of accessibility calculations. Underprivileged population often have specific needs that needs to be considered separately from the general commuting demand analysis, such as healthcare access for older or disabled users, or access to education in the case of younger residents.

While the methodology in this paper is straightforward, it is not without its drawbacks as described above. Therefore, future research could aim to improve the computation methods to more realistically reflect the accessibility decay during disruptions. Moreover, refining the spatial unit could also bring drastic improvements to the model, especially since population distribution data in fine grid cells is publicly available, which means population could be mapped to nearest transit stops and then calculate accessibility decay between stops instead of municipalities.

Besides, whereas Equation 3.1 takes weighted travel times as input values, the nature of AR_i as a ratio means that it is versatile and can be easily adapted to different accessibility measurement methods such as utility-based measurements. This is especially true as utility-based measurements have the advantage of capturing aspects of perceived accessibility, which needs to be concurrently considered besides objective accessibility measures (Lättman et al., 2018).

Policymakers should, as recommended by existing literature such as Keeling (2008), also focus on social inequity issues when planning transportation systems and policies. The findings from this thesis echoed with previous studies in that transit-reliant users are more vulnerable to transit service disruptions. The methodology used in this paper allows planners to conveniently assess both areas and user groups that are more vulnerable to disruptions, and thus assists them to remedy existing deficiencies in the network such that the public transit system is more resilient and equitable. This is especially essential during unplanned disruptions or emergencies when rapid response is needed. Public transit operators and coordinators, such as the Munich S-Bahn and the MVV, should take advantage of methods used in research to identify inequalities within the transit-dependent population, and develop strategies to compensate them during disruptions to prevent these users from being socially excluded.

A Percentages of underprivileged population segments for each municipality in the study area

Municipality	County	Unemployed (%)	Disabled (%)	Low-income (%)	Older (%)	Younger (%)
Adelshofen	Fürstenfeldbruck	0.629	6.346	19.752	17.496	13.265
Allershausen	Freising	1.079	5.120	21.210	13.904	14.127
Alling	Fürstenfeldbruck	0.787	6.014	18.336	19.614	12.890
Althegnenberg	Fürstenfeldbruck	1.261	7.517	23.311	17.459	12.706
Altomünster	Dachau	0.854	8.178	21.849	19.912	12.852
Andechs	Starnberg	0.741	6.506	18.631	18.857	12.113
Anzing	Ebersberg	0.958	6.635	18.174	18.650	13.087
Aschheim	München	1.247	5.265	19.545	15.721	13.174
Aßling	Ebersberg	0.817	6.116	21.983	18.260	14.197
Attenkirchen	Freising	1.029	6.070	20.282	15.655	14.874
Au i.d.Hallertau	Freising	1.240	7.079	21.192	17.142	14.109
Aying	München	1.107	5.849	21.402	15.609	12.048
Bad Heilbrunn	Bad Tölz-Wolfratshausen	0.833	7.347	19.768	20.071	12.497
Bad Tölz	Bad Tölz-Wolfratshausen	1.587	9.992	24.419	23.336	13.182
Baierbrunn	München	1.162	5.567	19.676	19.088	10.217
Baiern	Ebersberg	0.999	5.260	23.198	13.715	17.443
Benediktbeuern	Bad Tölz-Wolfratshausen	0.861	8.384	21.389	24.764	13.826
Berg	Starnberg	0.988	5.096	22.021	20.997	14.071
Bergkirchen	Dachau	0.720	5.647	20.421	16.902	12.542
Berglern	Erding	1.274	5.164	18.411	11.268	15.560
Bichl	Bad Tölz-Wolfratshausen	0.929	6.192	19.808	17.868	14.109
Bockhorn	Erding	0.837	5.684	18.144	15.207	14.001
Bruck	Ebersberg	0.311	6.599	21.463	18.168	14.286
Brunnthal	München	0.905	5.772	18.510	16.103	11.417
Buch a.Buchrain	Erding	0.657	6.509	18.447	18.738	11.966
Dachau	Dachau	1.266	7.881	20.456	18.929	14.457
Dietramszell	Bad Tölz-Wolfratshausen	0.908	4.650	20.213	17.566	14.696
Dorfen	Erding	1.102	8.145	21.636	19.256	14.615
Ebersberg	Ebersberg	1.001	8.808	20.725	22.029	12.942
Eching	Freising	1.049	6.079	20.426	17.667	16.190
Egenhofen	Fürstenfeldbruck	0.886	6.032	18.694	18.353	13.179
Egling	Bad Tölz-Wolfratshausen	0.768	4.812	21.191	18.789	12.935
Egmating	Ebersberg	0.761	5.711	22.593	16.709	12.098

Municipality	County	Unemployed (%)	Disabled (%)	Low-income (%)	Older (%)	Younger (%)
Eichenau	Fürstenfeldbruck	1.174	8.472	20.986	26.061	11.718
Eitting	Erding	0.903	4.896	17.751	12.049	15.000
Emmering	Ebersberg	0.928	7.029	22.296	19.231	14.456
Emmering	Fürstenfeldbruck	1.430	7.446	20.652	20.879	13.152
Erding	Erding	1.422	8.104	19.563	18.407	14.375
Erdweg	Dachau	0.984	6.607	17.791	17.115	13.262
Eurasburg	Bad Tölz-Wolfratshausen	0.864	5.954	20.118	18.819	12.888
Fahrenzhausen	Freising	0.955	5.770	19.604	14.604	13.729
Feldafing	Starnberg	1.179	7.805	20.893	27.847	12.167
Feldkirchen	München	1.112	5.310	17.358	12.897	12.262
Finsing	Erding	1.065	5.988	19.077	15.470	13.041
Forstern	Erding	0.893	4.953	19.575	13.884	13.640
Forstinning	Ebersberg	0.803	6.579	20.507	17.845	13.701
Frauenneuharting	Ebersberg	1.015	5.644	22.347	15.726	15.663
Fraunberg	Erding	0.668	5.612	19.176	16.221	13.041
Freising	Freising	1.512	6.687	24.339	15.289	19.851
Fürstenfeldbruck	Fürstenfeldbruck	1.803	9.088	21.699	20.919	14.077
Gaißach	Bad Tölz-Wolfratshausen	0.775	6.748	20.567	18.631	14.143
Gammelsdorf	Freising	1.027	6.366	18.133	16.359	10.951
Garching b.München	München	1.329	7.168	25.335	17.337	20.197
Gauting	Starnberg	1.117	6.665	20.886	22.380	12.209
Geltendorf	Landsberg am Lech	1.198	6.347	18.868	18.523	13.821
Geretsried	Bad Tölz-Wolfratshausen	1.411	9.572	24.149	22.529	12.768
Germering	Fürstenfeldbruck	1.401	8.389	20.445	23.451	12.839
Gilching	Starnberg	1.242	6.895	19.877	20.502	12.443
Glonn	Ebersberg	0.824	6.483	20.522	19.037	12.217
Gräfelfing	München	1.046	6.690	21.634	23.754	12.974
Grafing b.München	Ebersberg	1.154	7.412	21.476	20.907	14.171
Grafrath	Fürstenfeldbruck	0.903	7.639	19.497	23.587	11.303
Grasbrunn	München	0.881	5.572	18.673	17.468	11.665
Greiling	Bad Tölz-Wolfratshausen	0.814	6.581	18.642	21.031	13.772
Gröbenzell	Fürstenfeldbruck	1.213	7.564	20.278	24.619	11.783
Grünwald	München	0.843	5.963	19.134	25.626	10.603

Municipality	County	Unemployed (%)	Disabled (%)	Low-income (%)	Older (%)	Younger (%)
Haag a.d.Amper	Freising	0.809	5.767	19.730	16.560	14.233
Haar	München	1.425	9.066	20.520	20.898	13.615
Haimhausen	Dachau	0.872	5.863	18.019	16.891	13.401
Hallbergmoos	Freising	1.046	5.282	18.098	10.898	15.080
Hattenhofen	Fürstenfeldbruck	1.099	7.434	19.775	17.970	12.864
Hebertshausen	Dachau	0.944	7.043	18.952	18.909	13.212
Herrsching a.Ammersee	Starnberg	1.391	8.076	22.829	25.432	11.726
Hilgertshausen-Tandern	Dachau	0.846	6.711	18.913	18.062	13.306
Hohenbrunn	München	1.036	6.010	23.070	19.884	12.896
Hohenkammer	Freising	0.835	4.784	16.284	14.655	12.263
Höhenkirchen-Siegertsbrunn	München	1.213	6.011	19.894	17.969	12.904
Hohenlinden	Ebersberg	0.747	6.596	19.419	16.024	15.432
Hohenpolding	Erding	0.945	7.561	22.017	17.958	13.611
Holzkirchen	Miesbach	1.100	6.701	20.749	18.389	13.450
Hörgertshausen	Freising	1.103	7.623	18.555	17.503	14.443
Icking	Bad Tölz-Wolfratshausen	0.759	5.233	20.108	22.370	12.825
Inning a.Ammersee	Starnberg	1.159	5.983	21.484	21.449	10.787
Inning a.Holz	Erding	0.808	7.066	20.885	18.371	12.584
Isen	Erding	0.891	6.974	20.558	18.506	12.491
Ismaning	München	1.042	7.315	18.675	19.751	13.657
Jachenau	Bad Tölz-Wolfratshausen	0.697	6.156	18.500	19.280	12.079
Jesenwang	Fürstenfeldbruck	1.146	7.575	17.912	23.043	11.649
Karlsfeld	Dachau	1.177	7.901	20.095	19.966	12.898
Kirchberg	Erding	0.842	7.297	18.010	15.716	15.154
Kirchdorf a.d.Amper	Freising	1.014	4.545	19.792	13.053	15.356
Kirchheim b.München	München	1.093	7.228	20.829	24.791	11.763
Kirchseeon	Ebersberg	1.437	7.551	21.455	18.295	14.444
Kochel a.See	Bad Tölz-Wolfratshausen	1.537	7.978	25.098	24.055	12.027
Königsdorf	Bad Tölz-Wolfratshausen	0.830	5.651	18.066	18.838	12.867
Kottgeisering	Fürstenfeldbruck	0.684	6.468	18.636	21.580	11.443
Krailling	Starnberg	1.119	7.576	20.549	25.219	11.796
Kranzberg	Freising	0.963	5.275	19.991	18.401	14.186
Landsberied	Fürstenfeldbruck	0.806	6.324	16.828	16.243	13.329

Municipality	**County**	**Unemployed (%)**	**Disabled (%)**	**Low-income (%)**	**Older (%)**	**Younger (%)**
Langenbach	Freising	0.965	6.807	25.688	16.485	14.926
Langenpreising	Erding	0.908	6.110	19.439	16.341	13.268
Lengdorf	Erding	0.877	5.263	19.734	16.849	14.510
Lenggries	Bad Tölz-Wolfratshausen	0.926	7.464	21.898	22.860	12.102
Maisach	Fürstenfeldbruck	1.210	7.941	20.114	19.184	13.391
Mammendorf	Fürstenfeldbruck	1.263	6.066	19.433	15.694	15.321
Markt Indersdorf	Dachau	0.866	7.328	20.430	19.852	14.703
Markt Schwaben	Ebersberg	1.172	7.128	19.215	17.079	13.888
Marzling	Freising	0.962	6.762	21.994	16.160	14.578
Mauern	Freising	0.832	5.890	20.814	17.542	12.612
Mittelstetten	Fürstenfeldbruck	1.401	7.122	21.934	19.848	11.267
Moorenweis	Fürstenfeldbruck	1.034	6.324	18.878	17.432	13.248
Moosach	Ebersberg	0.929	6.171	19.750	15.793	12.210
Moosburg a.d.Isar	Freising	1.517	8.855	23.918	18.643	14.794
Moosinning	Erding	1.101	5.839	19.197	15.849	14.014
München	München	2.059	7.580	21.907	17.456	17.156
Münsing	Bad Tölz-Wolfratshausen	0.748	5.004	18.932	20.856	12.111
Nandlstadt	Freising	1.357	7.953	23.042	17.490	13.645
Neubiberg	München	0.643	5.695	15.907	16.814	24.829
Neuching	Erding	0.975	5.664	17.772	14.854	13.541
Neufahrn b.Freising	Freising	1.270	6.834	22.101	16.578	16.221
Neuried	München	1.009	6.773	19.791	19.807	12.965
Oberding	Erding	0.814	5.288	18.506	13.611	15.316
Oberhaching	München	0.960	6.286	19.767	20.851	12.834
Oberpframmern	Ebersberg	0.818	6.465	18.407	17.349	13.666
Oberschleißheim	München	1.318	8.730	22.869	21.601	14.730
Oberschweinbach	Fürstenfeldbruck	0.698	7.974	21.634	20.838	12.049
Odelzhausen	Dachau	1.190	7.080	19.202	17.340	12.463
Olching	Fürstenfeldbruck	1.283	7.643	19.815	19.564	12.650
Ottenhofen	Erding	0.877	5.879	19.712	15.678	13.306
Otterfing	Miesbach	0.911	5.548	19.396	18.733	12.627
Ottobrunn	München	1.300	7.799	18.874	21.997	12.755
Pastetten	Erding	0.799	7.260	19.334	15.535	14.374

Municipality	County	Unemployed (%)	Disabled (%)	Low-income (%)	Older (%)	Younger (%)
Paunzhausen	Freising	1.254	6.799	18.061	15.380	13.399
Petershausen	Dachau	1.070	8.012	19.508	18.930	13.287
Pfaffenhofen a.d.Glonn	Dachau	0.668	5.699	16.479	15.850	13.313
Planegg	München	1.198	7.090	20.712	22.838	14.649
Pliening	Ebersberg	0.791	5.712	16.757	15.237	12.759
Pöcking	Starnberg	1.304	7.270	21.181	26.652	11.665
Poing	Ebersberg	1.054	6.054	17.989	13.472	13.075
Puchheim	Fürstenfeldbruck	1.606	7.942	21.278	23.696	12.252
Pullach i.Isartal	München	0.952	6.523	20.990	23.654	11.573
Putzbrunn	München	1.181	8.387	19.106	22.006	11.287
Reichersbeuern	Bad Tölz-Wolfratshausen	0.856	4.853	19.714	16.476	16.150
Röhrmoos	Dachau	0.884	14.804	23.838	18.633	13.517
Rudelzhausen	Freising	0.863	6.676	22.765	16.892	14.446
Sachsenkam	Bad Tölz-Wolfratshausen	0.854	4.193	21.114	16.227	14.907
Sankt Wolfgang	Erding	0.737	7.746	20.360	17.634	13.862
Sauerlach	München	0.936	5.931	18.497	18.960	11.534
Schäftlarn	München	0.941	5.662	21.821	23.076	11.427
Schlehdorf	Bad Tölz-Wolfratshausen	0.695	7.259	22.467	20.618	15.444
Schöngeising	Fürstenfeldbruck	1.259	7.132	20.297	22.549	11.589
Schwabhausen	Dachau	0.953	5.947	20.494	17.689	13.170
Seefeld	Starnberg	1.072	5.839	21.869	22.137	11.916
Starnberg	Starnberg	1.277	7.429	20.865	23.395	12.117
Steinhöring	Ebersberg	0.946	9.069	24.718	17.410	14.113
Steinkirchen	Erding	1.030	7.052	20.881	18.859	15.372
Straßlach-Dingharting	München	1.045	4.917	19.939	21.174	10.633
Sulzemoos	Dachau	0.939	4.919	23.844	13.495	14.207
Taufkirchen	München	1.789	9.544	22.755	26.165	12.444
Taufkirchen (Vils)	Erding	0.962	8.737	23.325	18.795	13.528
Türkenfeld	Fürstenfeldbruck	1.139	6.316	20.772	18.921	13.256
Tutzing	Starnberg	1.190	7.028	20.874	26.033	11.182
Unterföhring	München	1.276	6.549	20.237	15.686	12.912
Unterhaching	München	1.309	8.222	18.669	22.634	11.489
Unterschleißheim	München	1.392	8.169	20.721	18.781	14.079

Municipality	County	Unemployed (%)	Disabled (%)	Low-income (%)	Older (%)	Younger (%)
Valley	Miesbach	0.947	5.625	20.854	17.111	13.410
Vaterstetten	Ebersberg	0.959	6.937	19.323	21.513	12.031
Vierkirchen	Dachau	0.884	8.197	20.857	17.796	13.395
Wackersberg	Bad Tölz-Wolfratshausen	0.828	6.139	19.291	19.617	14.792
Walpertskirchen	Erding	0.743	5.483	17.477	15.613	15.660
Wang	Freising	1.028	5.929	21.429	15.099	14.229
Wartenberg	Erding	1.153	7.333	19.993	17.189	13.225
Weichs	Dachau	1.021	7.315	21.274	20.017	13.864
Weßling	Starnberg	1.094	5.397	22.308	21.477	12.799
Wolfersdorf	Freising	1.038	5.419	25.292	13.182	14.489
Wolfratshausen	Bad Tölz-Wolfratshausen	1.256	7.545	21.165	22.267	12.641
Wörth	Erding	1.224	6.889	19.733	17.902	14.775
Wörthsee	Starnberg	1.006	5.753	20.078	22.651	10.742
Zolling	Freising	1.029	6.462	20.421	16.938	13.521
Zorneding	Ebersberg	0.972	7.331	20.383	22.077	12.374

B Accessibility ratios for each municipality in the study area

Municipality	**County**	AR_i	$I_{i,unemployed}$	$I_{i,disabled}$	$I_{i,low-income}$	$I_{i,older}$	$I_{i,younger}$
Adelshofen	Fürstenfeldbruck	1.0024	0.6305	6.3619	19.7996	17.5381	13.2969
Allershausen	Freising	1.0026	1.0816	5.1333	21.2660	13.9407	14.1639
Alling	Fürstenfeldbruck	1.0435	0.8208	6.2753	19.1332	20.4674	13.4508
Althegnenberg	Fürstenfeldbruck	1.0207	1.2870	7.6723	23.7928	17.8195	12.9686
Altomünster	Dachau	1.0130	0.8654	8.2846	22.1324	20.1707	13.0187
Anzing	Ebersberg	1.1125	1.0654	7.3815	20.2197	20.7493	14.5600
Aschheim	München	1.1010	1.3724	5.7971	21.5183	17.3085	14.5046
Aßling	Ebersberg	1.0346	0.8452	6.3275	22.7433	18.8912	14.6881
Attenkirchen	Freising	1.0064	1.0360	6.1089	20.4115	15.7546	14.9687
Au i.d.Hallertau	Freising	1.0023	1.2425	7.0954	21.2418	17.1826	14.1417
Aying	München	1.0032	1.1105	5.8672	21.4694	15.6583	12.0861
Baiern	Ebersberg	0.9926	0.9912	5.2205	23.0254	13.6131	17.3137
Berg	Starnberg	1.0004	0.9882	5.0979	22.0300	21.0063	14.0765
Bergkirchen	Dachau	0.9995	0.7200	5.6441	20.4102	16.8936	12.5352
Berglern	Erding	1.0013	1.2760	5.1712	18.4360	11.2827	15.5809
Bruck	Ebersberg	1.0386	0.3225	6.8539	22.2904	18.8684	14.8367
Brunnthal	München	1.0067	0.9107	5.8104	18.6340	16.2110	11.4934
Buch a.Buchrain	Erding	1.0397	0.6836	6.7672	19.1786	19.4812	12.4406
Dachau	Dachau	0.9845	1.2461	7.7592	20.1398	18.6357	14.2331
Dorfen	Erding	0.9975	1.0995	8.1242	21.5821	19.2076	14.5788
Ebersberg	Ebersberg	1.0597	1.0603	9.3343	21.9627	23.3445	13.7147
Eching	Freising	0.9730	1.0206	5.9152	19.8751	17.1902	15.7530
Egenhofen	Fürstenfeldbruck	1.0041	0.8899	6.0568	18.7706	18.4288	13.2332
Egling	Bad Tölz-Wolfratshausen	1.0145	0.7796	4.8815	21.4996	19.0622	13.1226
Egmating	Ebersberg	1.0201	0.7767	5.8252	23.0460	17.0441	12.3408
Eichenau	Fürstenfeldbruck	0.8394	0.9857	7.1113	17.6163	21.8759	9.8361
Eitting	Erding	0.9777	0.8827	4.7869	17.3556	11.7804	14.6661
Emmering	Ebersberg	1.0238	0.9505	7.1965	22.8272	19.6886	14.8004
Emmering	Fürstenfeldbruck	0.9999	1.4301	7.4451	20.6495	20.8758	13.1506
Erding	Erding	1.0627	1.5108	8.6125	20.7889	19.5610	15.2767
Erdweg	Dachau	0.9999	0.9835	6.6060	17.7893	17.1133	13.2612
Eurasburg	Bad Tölz-Wolfratshausen	1.0100	0.8725	6.0131	20.3182	19.0060	13.0165
Fahrenzhausen	Freising	1.0284	0.9822	5.9341	20.1620	15.0195	14.1191

Municipality	County	AR_i	$I_{i,unemployed}$	$I_{i,disabled}$	$I_{i,low-income}$	$I_{i,older}$	$I_{i,younger}$
Feldafing	Starnberg	0.9796	1.1549	7.6454	20.4662	27.2785	11.9185
Feldkirchen	München	1.2971	1.4427	6.8872	22.5148	16.7285	15.9041
Finsing	Erding	1.0934	1.1649	6.5470	20.8596	16.9149	14.2589
Forstern	Erding	1.0044	0.8970	4.9744	19.6606	13.9445	13.6999
Forstinning	Ebersberg	1.0026	0.8050	6.5956	20.5598	17.8912	13.7365
Frauenneuharting	Ebersberg	1.0371	1.0523	5.8531	23.1767	16.3099	16.2441
Fraunberg	Erding	0.9866	0.6591	5.5367	18.9186	16.0036	12.8661
Freising	Freising	1.0003	1.5128	6.6887	24.3451	15.2933	19.8563
Fürstenfeldbruck	Fürstenfeldbruck	0.9998	1.8022	9.0868	21.6955	20.9162	14.0747
Garching b.München	München	1.0760	1.4298	7.7125	27.2599	18.6542	21.7320
Gauting	Starnberg	0.9721	1.0862	6.4797	20.3045	21.7567	11.8686
Geretsried	Bad Tölz-Wolfratshausen	1.0096	1.4248	9.6641	24.3810	22.7454	12.8908
Germering	Fürstenfeldbruck	1.1039	1.5466	9.2605	22.5693	25.8878	14.1735
Gilching	Starnberg	1.0495	1.3037	7.2363	20.8610	21.5171	13.0593
Glonn	Ebersberg	1.0147	0.8366	6.5784	20.8238	19.3168	12.3962
Gräfelfing	München	0.9646	1.0090	6.4536	20.8684	22.9135	12.5149
Grafing b.München	Ebersberg	1.0671	1.2317	7.9090	22.9163	22.3093	15.1208
Grafrath	Fürstenfeldbruck	1.0010	0.9041	7.6465	19.5164	23.6111	11.3147
Grasbrunn	München	1.1095	0.9770	6.1825	20.7176	19.3804	12.9416
Gröbenzell	Fürstenfeldbruck	1.0046	1.2188	7.5985	20.3703	24.7316	11.8367
Grünwald	München	0.9857	0.8309	5.8773	18.8602	25.2585	10.4515
Haag a.d.Amper	Freising	1.0003	0.8097	5.7689	19.7358	16.5644	14.2366
Haar	München	1.2173	1.7345	11.0362	24.9801	25.4394	16.5742
Haimhausen	Dachau	1.0467	0.9132	6.1369	18.8612	17.6802	14.0272
Hallbergmoos	Freising	1.0465	1.0943	5.5280	18.9399	11.4050	15.7821
Hattenhofen	Fürstenfeldbruck	1.0015	1.1006	7.4450	19.8048	17.9976	12.8831
Hebertshausen	Dachau	0.9990	0.9428	7.0358	18.9326	18.8902	13.1987
Herrsching a.Ammersee	Starnberg	1.0249	1.4257	8.2769	23.3971	26.0650	12.0182
Hilgertshausen-Tandern	Dachau	0.9997	0.8460	6.7094	18.9072	18.0570	13.3021
Hohenkammer	Freising	1.0000	0.8352	4.7836	16.2841	14.6545	12.2627
Höhenkirchen-Siegertsbrunn	München	1.0166	1.2334	6.1109	20.2244	18.2673	13.1188
Hohenlinden	Ebersberg	1.0024	0.7485	6.6121	19.4656	16.0624	15.4698
Holzkirchen	Miesbach	1.0013	1.1011	6.7091	20.7748	18.4124	13.4664

Municipality	County	AR_i	$I_{i,unemployed}$	$I_{i,disabled}$	$I_{i,low-income}$	$I_{i,older}$	$I_{i,younger}$
Icking	Bad Tölz-Wolfratshausen	1.0178	0.7727	5.3264	20.4661	22.7682	13.0537
Inning a.Ammersee	Starnberg	1.0089	1.1698	6.0370	21.6761	21.6412	10.8833
Inning a.Holz	Erding	0.9624	0.7771	6.8000	20.0985	17.6800	12.1105
Isen	Erding	1.0438	0.9300	7.2792	21.4576	19.3157	13.0381
Ismaning	München	1.1332	1.1804	8.2888	21.1623	22.3818	15.4755
Jesenwang	Fürstenfeldbruck	1.0033	1.1496	7.5999	17.9717	23.1189	11.6872
Karlsfeld	Dachau	0.9663	1.1375	7.6348	19.4171	19.2929	12.4636
Kirchdorf a.d.Amper	Freising	1.0026	1.0161	4.5572	19.8434	13.0865	15.3959
Kirchheim b.München	München	1.1666	1.2749	8.4325	24.2990	28.9218	13.7233
Kirchseeon	Ebersberg	1.0845	1.5583	8.1887	23.2682	19.8403	15.6645
Königsdorf	Bad Tölz-Wolfratshausen	1.0059	0.8350	5.6847	18.1731	18.9490	12.9431
Kottgeisering	Fürstenfeldbruck	0.9991	0.6835	6.4619	18.6191	21.5602	11.4325
Landsberied	Fürstenfeldbruck	0.9997	0.8057	6.3216	16.8227	16.2378	13.3249
Langenbach	Freising	1.0020	0.9673	6.8207	25.7405	16.5186	14.9560
Langenpreising	Erding	0.9923	0.9009	6.0635	19.2901	16.2155	13.1664
Lengdorf	Erding	0.9977	0.8752	5.2512	19.6892	16.8111	14.4773
Mammendorf	Fürstenfeldbruck	1.0098	1.2753	6.1255	19.6228	15.8470	15.4707
Markt Indersdorf	Dachau	1.0016	0.8674	7.3392	20.4621	19.8825	14.7260
Markt Schwaben	Ebersberg	1.1035	1.2937	7.8659	21.2033	18.8461	15.3244
Marzling	Freising	1.0185	0.9794	6.8871	22.4019	16.4595	14.8483
Mittelstetten	Fürstenfeldbruck	1.0015	1.4031	7.1326	21.9665	19.8777	11.2835
Moorenweis	Fürstenfeldbruck	0.9996	1.0335	6.3211	18.8700	17.4251	13.2431
Moosach	Ebersberg	1.0549	0.9800	6.5098	20.8337	16.6595	12.8796
Moosburg a.d.Isar	Freising	1.0001	1.5172	8.8564	23.9216	18.6456	14.7964
Moosinning	Erding	1.0766	1.1854	6.2864	20.6677	17.0630	15.0873
München	München	1.0726	2.2083	8.1301	23.4976	18.7234	18.4013
Nandlstadt	Freising	1.0013	1.3587	7.9633	23.0712	17.5117	13.6621
Neubiberg	München	1.0462	0.6723	5.9583	16.6423	17.5917	25.9772
Neuching	Erding	1.0410	1.0153	5.8963	18.5008	15.4631	14.0964
Neufahrn b.Freising	Freising	0.9806	1.2449	6.7013	21.6727	16.2571	15.9070
Neuried	München	0.9650	0.9736	6.5352	19.0971	19.1133	12.5109
Oberding	Erding	0.9660	0.7858	5.1079	17.8761	13.1476	14.7948
Oberhaching	München	1.0610	1.0189	6.6691	20.9719	22.1222	13.6160

Municipality	**County**	AR_i	$I_{i,unemployed}$	$I_{i,disabled}$	$I_{i,low-income}$	$I_{i,older}$	$I_{i,younger}$
Oberpframmern	Ebersberg	1.0301	0.8429	6.6592	18.9607	17.8703	14.0770
Oberschleißheim	München	1.0023	1.3214	8.7498	22.9217	21.6501	14.7637
Oberschweinbach	Fürstenfeldbruck	1.0089	0.7047	8.0455	21.8269	21.0239	12.1563
Odelzhausen	Dachau	0.9932	1.1817	7.0322	19.0720	17.2222	12.3790
Olching	Fürstenfeldbruck	0.9968	1.2787	7.6190	19.7519	19.5015	12.6092
Ottenhofen	Erding	1.0736	0.9412	6.3119	21.1617	16.8316	14.2847
Otterfing	Miesbach	1.0042	0.9146	5.5709	19.4777	18.8120	12.6799
Ottobrunn	München	1.0355	1.3461	8.0766	19.5452	22.7787	13.2080
Pastetten	Erding	1.0594	0.8460	7.6905	20.4815	16.4576	15.2271
Paunzhausen	Freising	1.0008	1.2551	6.8039	18.0745	15.3914	13.4096
Petershausen	Dachau	1.0170	1.0885	8.1482	19.8391	19.2509	13.5130
Planegg	München	0.9719	1.1646	6.8910	20.1307	22.1967	14.2374
Pliening	Ebersberg	1.0854	0.8584	6.1993	18.1875	16.5379	13.8484
Pöcking	Starnberg	1.0106	1.3179	7.3477	21.4057	26.9354	11.7888
Poing	Ebersberg	1.1666	1.2301	7.0621	20.9849	15.7162	15.2531
Puchheim	Fürstenfeldbruck	1.0054	1.6148	7.9849	21.3920	23.8232	12.3177
Pullach i.Isartal	München	1.0461	0.9963	6.8234	21.9575	24.7450	12.1061
Putzbrunn	München	1.0312	1.2179	8.6484	19.7020	22.6924	11.6391
Röhrmoos	Dachau	0.9963	0.8803	14.7497	23.7508	18.5646	13.4678
Sankt Wolfgang	Erding	0.9938	0.7321	7.6976	20.2339	17.5249	13.7759
Sauerlach	München	1.0241	0.9584	6.0741	18.9438	19.4172	11.8121
Schäftlarn	München	1.0315	0.9704	5.8402	22.5072	23.8018	11.7862
Schöngeising	Fürstenfeldbruck	0.9972	1.2549	7.1114	20.2394	22.4845	11.5560
Schwabhausen	Dachau	0.9968	0.9498	5.9287	20.4295	17.6329	13.1289
Seefeld	Starnberg	1.0227	1.0968	5.9713	22.3653	22.6393	12.1862
Starnberg	Starnberg	0.9998	1.2770	7.4279	20.8606	23.3903	12.1144
Steinhöring	Ebersberg	1.0000	0.9457	9.0689	24.7176	17.4103	14.1125
Sulzemoos	Dachau	0.9874	0.9267	4.8573	23.5444	13.3256	14.0286
Taufkirchen	München	1.0625	1.9007	10.1408	24.1781	27.8015	13.2220
Taufkirchen (Vils)	Erding	0.9970	0.9592	8.7106	23.2558	18.7390	13.4874
Türkenfeld	Fürstenfeldbruck	0.9997	1.1382	6.3144	20.7664	18.9161	13.2521
Tutzing	Starnberg	1.0054	1.1962	7.0657	20.9868	26.1744	11.2422
Unterföhring	München	1.1816	1.5079	7.7385	23.9127	18.5347	15.2571

Municipality	**County**	AR_i	$I_{i,unemployed}$	$I_{i,disabled}$	$I_{i,low-income}$	$I_{i,older}$	$I_{i,younger}$
Unterhaching	München	1.0833	1.4182	8.9075	20.2248	24.5201	12.4464
Unterschleißheim	München	0.9681	1.3477	7.9090	20.0606	18.1823	13.6309
Vaterstetten	Ebersberg	1.1396	1.0927	7.9056	22.0199	24.5152	13.7099
Vierkirchen	Dachau	0.9968	0.8815	8.1703	20.7897	17.7382	13.3520
Walpertskirchen	Erding	0.9966	0.7410	5.4645	17.4168	15.5600	15.6063
Wartenberg	Erding	0.9863	1.1374	7.2330	19.7199	16.9541	13.0443
Weichs	Dachau	1.0002	1.0210	7.3168	21.2796	20.0220	13.8679
Weßling	Starnberg	1.0358	1.1330	5.5895	23.1055	22.2449	13.2563
Wolfersdorf	Freising	1.0013	1.0390	5.4259	25.3247	13.1991	14.5075
Wolfratshausen	Bad Tölz-Wolfratshausen	1.0115	1.2702	7.6318	21.4089	22.5233	12.7869
Wörthsee	Starnberg	1.0247	1.0306	5.8952	20.5726	23.2098	11.0071
Zolling	Freising	1.0003	1.0293	6.4640	20.4264	16.9424	13.5251
Zorneding	Ebersberg	1.1201	1.0892	8.2110	22.8313	24.7286	13.8605

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