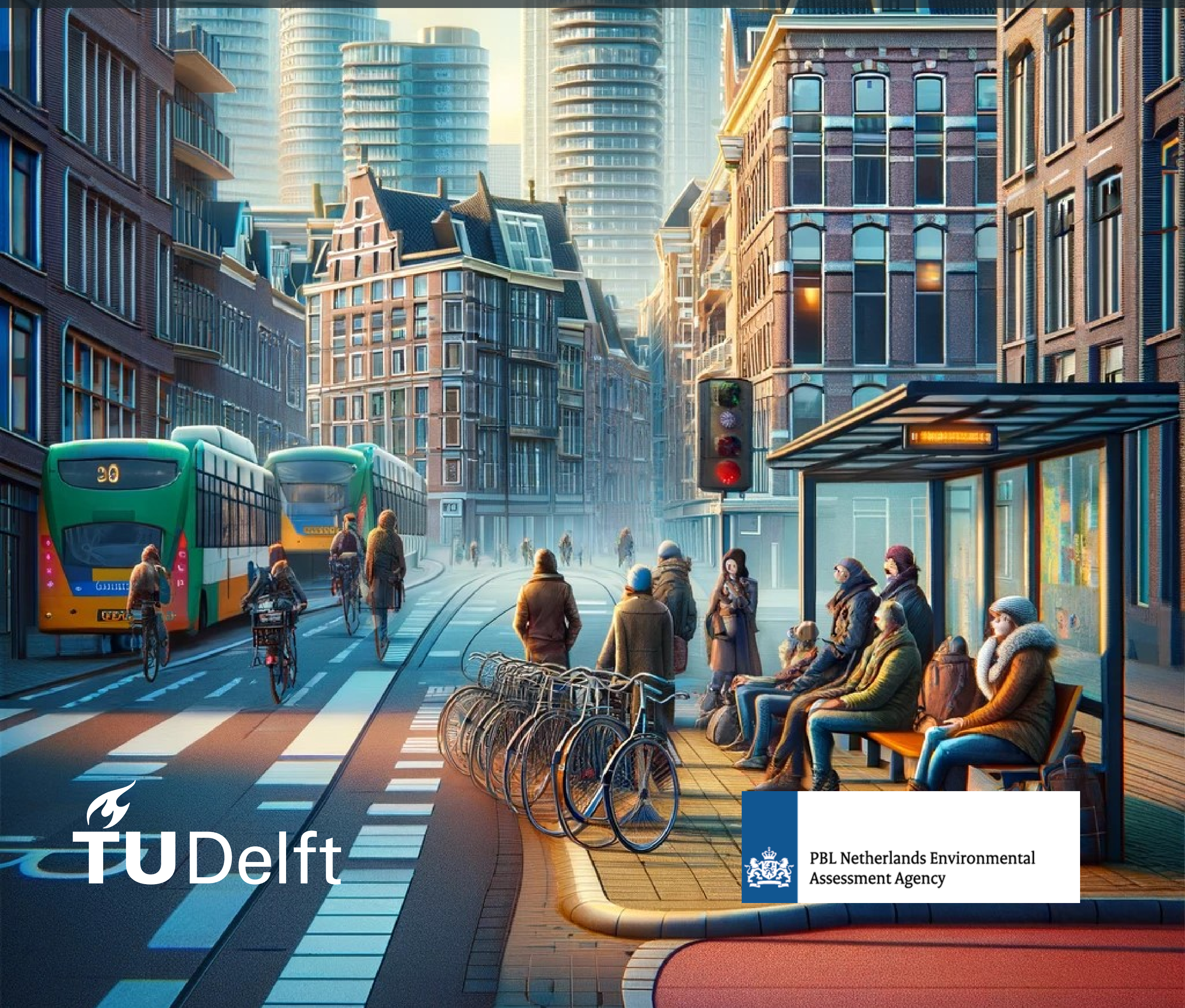
Transport accessibility and car availability barriers to out-of-home activity participation among the unemployed

A Dutch nationwide latent class cluster analysis

Thijs Bon



TU Delft

PBL Netherlands Environmental Assessment Agency

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A Dutch nationwide latent class cluster analysis

by

Thijs Bon

This research is done in partial fulfillment of the requirements for the degree of Master of Science in Civil Engineering – Transport and Planning

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Thesis assessment committee:

Chair:	Dr. Niels van Oort	CEG, Smart Public Transport Lab
Supervisors:	Dr. Matthew Bruno	CEG, Smart Public Transport Lab
	Dr. Maarten Kroesen	TPM, Transport and Logistics
External supervisor:	Dr. Jeroen Bastiaanssen	PBL, Urbanisation and Transport

Place:	Faculty Of Civil Engineering and Geosciences, Department of Transport & Planning, TU Delft
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Student number:	4342623

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Although my future career may lead me in a different direction, the skills and insights I have gained during this time are invaluable, equipping me to make meaningful contributions to society.

Summary

Transport-related social exclusion—a phenomenon where individuals are prevented from fully participating in society, primarily due to a lack of accessible opportunities, services, and social networks—emerges prominently in societies characterized by widespread car use, where many destinations become inaccessible to those unable to rely on a car. The intersection of transport and social disadvantage at the root of transport-related social exclusion, known as transport poverty, amplifies social inequality by isolating those already vulnerable due to financial, health, or physical constraints.

Previous research has established the role of transport in both social exclusion and labor market outcomes, highlighting the potential of transport and land use policies to counter social isolation and break cycles of economic and social marginalization by enhancing accessibility to various activities. However, a notable gap in the literature exists regarding the impact of transport disadvantage on the unemployed's participation in activities beyond the labor market.

Central to this thesis' contribution is the delineation of eight distinct groups mainly based on transport accessibility and car ownership among the unemployed, assessing how these factors are shaped by socio-demographic characteristics and how they influence engagement in various out-of-home activities, including shopping or groceries, social visits, and recreational activities. Furthermore, the residential urbanization context and travel behavior outcomes such as mode usage, travel period, daily travel time, and daily travel distance are presented and interpreted for each distinct group. By doing so, the thesis offers valuable insights into the complex mechanisms by which transport disadvantage is linked to reduced out-of-home activity participation among the unemployed.

Transport accessibility is examined through the number of accessible jobs (based on a log-logistic travel time decay function) by car, public transport, and bicycle. Car availability is analyzed through measures of car ownership, driver's license possession, and the number of cars in a household, recognizing its significant impact on spatial and temporal mobility.

Latent class cluster analysis is used to identify distinct patterns of transport accessibility and car availability among the unemployed to avoid imposing arbitrary definitions and sufficiency thresholds and to incorporate the socio-demographic determinants of transport

disadvantage. This approach enables an exploration of the heterogeneous experiences of transport disadvantage reflective of the existing patterns among the unemployed, highlighting the importance of socio-demographic factors in shaping these patterns.

The latent class cluster analysis reveals a broad spectrum of transport accessibility and car availability patterns among the unemployed in the Netherlands, ranging from low to medium to high. These patterns are organized into groups or clusters, as depicted in Figure 1. A notable absence in these patterns is the combination of high car availability with high accessibility. Some groups, particularly those with lower car availability, exhibit high accessibility, which is associated with living in highly urbanized areas. Another segment characterized by moderate accessibility features high car availability, with members primarily residing in strongly urbanized settings. Additionally, there are clusters with low accessibility, mostly in less urbanized residential locales, where high car availability is observed and essential for access. The analysis also identifies a specific subset experiencing compounded transport challenges, marked by both low car availability and low accessibility, despite their predominant residence in strongly or highly urbanized areas, highlighting a profound transport disadvantage.

The research contrasts out-of-home activity participation between unemployed and employed individuals with similar socio-demographic profiles, using propensity score matching to isolate the combined effect of employment status and non-socio-demographically determined transport disadvantage on out-of-home activity participation and travel behavior. This combined effect is presented through differences in out-of-home activity participation and travel behavior between the employment-status-differentiated groups for each of the eight patterns of transport accessibility and car availability among the unemployed.

Subsequently, the study conducts a comparative analysis of deficits in out-of-home activity engagement across the eight groups identified by their unique patterns of transport accessibility and car availability among the unemployed. This crucial comparison allows for the separation of the direct impact of transport disadvantage on activity engagement from the direct effects related to employment status. By adopting this detailed perspective, the research significantly deepens our comprehension of the dynamic interplay between transport accessibility, car availability, and employment status in influencing out-of-home activity participation.

The main discovery of this thesis is a compensatory mechanism among unemployed individuals, who tend to increase their participation in non-work-related activities as a potential means to counter the limitations of unemployment. However, this compensatory

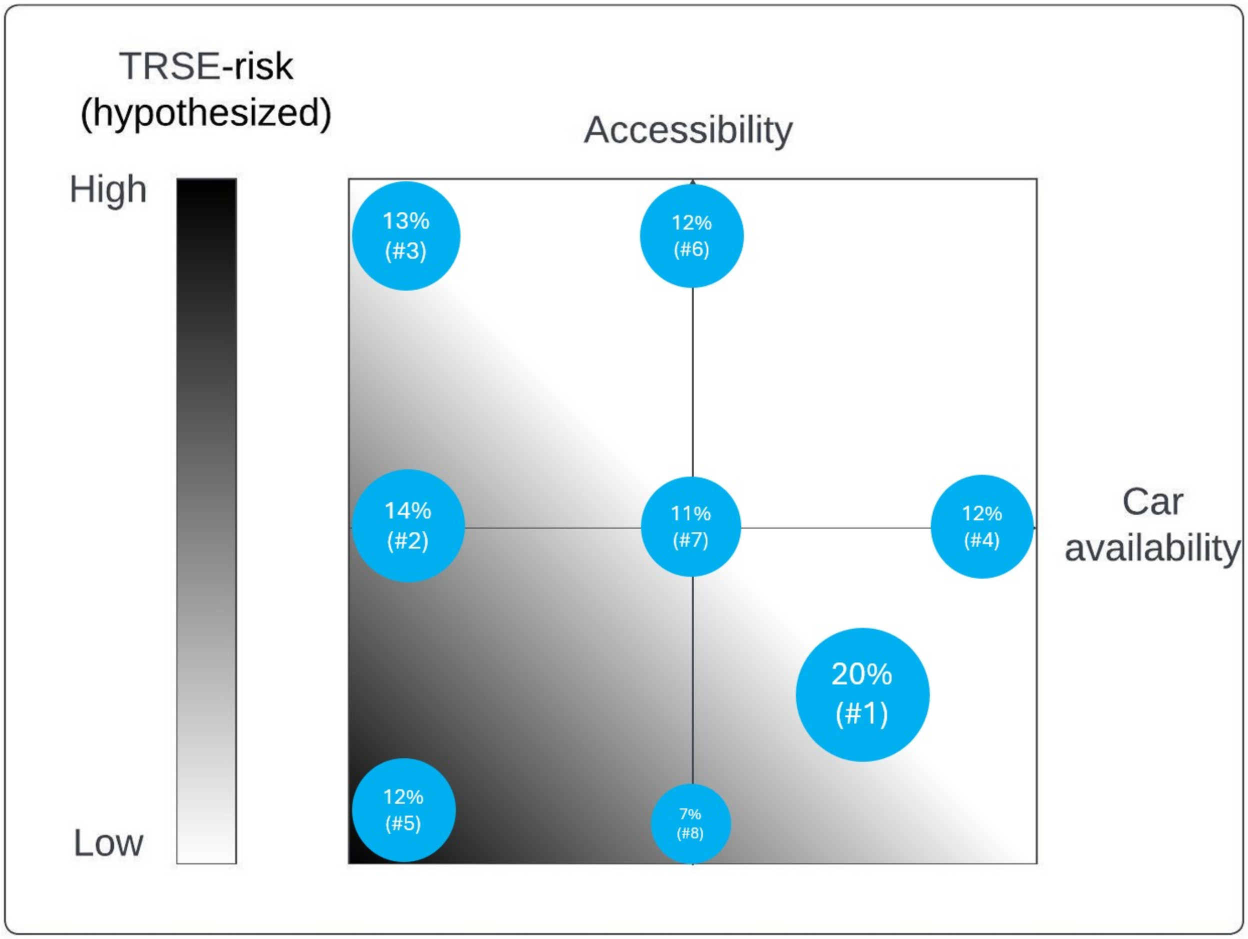

Figure 1: Mapping of each cluster onto the indicator-profiles-derived accessibility and car availability plane, on the backdrop of the hypothesized TRSE-risk due to transportation-limited out-of-home activity participation.
Note: Clusters are visualized as circles sized proportionally to their sample size percentages, with numbers indicating their size ranking from largest (#1) to smallest (#8).

behavior is not uniformly fully realized across all groups, specifically not among groups with low car availability, underscored by significant deficits in out-of-home activity participation. Surprisingly, accessibility does not seem to influence the differential in out-of-home activity participation between the unemployed and their socio-demographically-alike employed counterparts, suggesting that car availability is the primary dimension through which compensatory behavior is enabled.

This finding challenges the hypothesized compensatory relationship between transport accessibility and car availability and suggests that individuals with higher car availability, regardless of their level of accessibility, are at a lower risk of transport-related social exclusion, whereas those with low car availability exhibit a higher risk, irrespective of their accessibility levels.

The compensatory behavior observed among unemployed individuals—increasing their participation in non-work-related activities—varies not only with car availability but also aligns with socio-demographic traits, residential urbanization levels, activity types participated in, and travel behavior. Although the compensatory behavior is relative to socio-demographically-alike employed individuals, socio-demographic factors can still compound with employment status and transport disadvantage to inhibit the full expression of this compensatory mechanism.

The study reveals that, regardless of car availability, groceries or shopping constitute the majority of activities for each group of unemployed individuals. However, those with higher car availability typically engage more in social, recreational, and transporting people or goods activities—compared to the unemployed with lower car availability.

Groups with lower car availability, which represent 61% of the unemployed sample and typically have higher accessibility, often comprise younger people, individuals living in single-person households, those with lower household incomes, and individuals with a non-native (parental) birthplace, predominantly residing in highly urbanized areas. Marked in red in Figure 2, these socially-disadvantaged groups predominantly rely on active transportation modes, such as biking and walking, and to a lesser extent, public transport—reflecting not just transport disadvantage but also a connection with their younger age, lower household incomes, overrepresentation of single-person households, and residences in highly urbanized areas.

In contrast, the higher car availability groups, represented by the green clusters in Figure 2 and constituting 39% of the unemployed sample, are more likely to live in less urbanized settings with lower accessibility levels and to have beneficial socio-demographic traits like

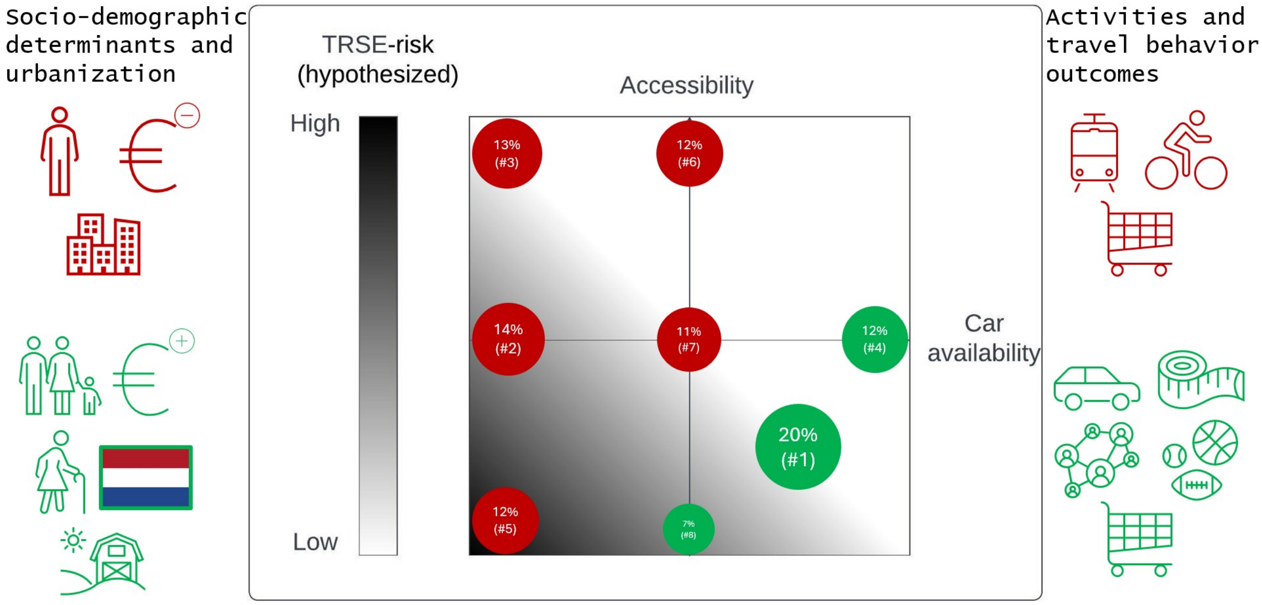

Figure 2: Mapping of each cluster onto the indicator-profiles-derived accessibility and car availability plane, with socio-demographic, residential urbanization level, activity participation, and travel behavior context.
Note: Clusters are visualized as circles sized proportionally to their sample size percentages, with numbers indicating their size ranking from largest (#1) to smallest (#8).

higher household incomes and the support structure of multi-person households, often coupled with native (parental) birthplace status. These generally older individuals mainly use the car and typically display longer daily travel distances, utilizing a similar amount of daily travel time as those with lower car availability but participating in more and a wider range of activities. Their car access and socio-demographic advantages seem to enable a full realization of the compensatory mechanism by engaging in more non-work-related activities as opposed to the low car availability groups. Thus, car availability intertwines with other socio-demographic and residential elements to distinctly shape the out-of-home activity participation and travel behavior of unemployed individuals.

This study, informed by existing literature on affordability limitations, recommends enhancing affordable transport accessibility for unemployed individuals with low car availability. It advises implementing subsidized public transport fares and travel allowances for low-household-income groups, thereby extending access to out-of-home activities beyond conventional walking and cycling distances. The research supports promoting mixed-use developments and enhancing infrastructure for active transportation modes to increase activity options within reachable distances for those with limited car availability. Additionally, it advocates for policy measures that are specifically designed to accommodate the unique needs of younger individuals, single-person households, and residents with a non-native (parental) birthplace. Such tailored initiatives, including community engagement programs that involve these residents in urban planning, are crucial for ensuring that development efforts are inclusive and effectively address specific demographic challenges.

Future research stemming from this study should delve deeper into the interconnections between transport disadvantage, social inclusion, unemployment, and other forms of social disadvantage. It should explore physical and digital in-home activities, subjective experiences of social inclusion, and the role of transport and housing expenses in shaping transport affordability.

Additionally, investigating compensatory behaviors across different levels of affordability, accessibility, and car availability is recommended. It should also be examined how household structure and other socio-demographic factors influence opportunities for engaging in compensatory activities for the unemployed. Future studies should consider employing panel data to effectively disentangle the long-term impacts of economic and transport factors from socio-demographic influences on social inclusion.

Adopting an interdisciplinary approach—integrating insights from transportation, urban planning, sociology, psychology, and economics—will be crucial for addressing the multifaceted challenges of unemployment and crafting effective policy interventions. Using instrumental variable analysis or natural experiments can enhance causal inferences about the effects of transport disadvantage and affordability on out-of-home activity participation, leading to more precise and effective policy interventions. Finally, to better distinguish group characteristics and clarify causal relationships in the findings, it is recommended to use other analytical methods like hierarchical clustering, K-means clustering, and structural equation modeling. These directions aim to enrich our understanding and support the development of comprehensive strategies for improving social inclusion among the unemployed.

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Introduction

Transport-related social exclusion (TRSE) or mobility-related exclusion is the process by which individuals are hindered from engaging in the economic, political, and social spheres of the community, primarily due to a lack of accessible opportunities, services, and social networks. This form of exclusion arises in a society and environment that presupposes high mobility, but fails to adequately provide it (Kenyon et al., 2002). Consequently, transport poverty emerges as a key barrier, potentially preventing people from accessing essential destinations such as employment, education, healthcare, and other vital services.

Transport poverty emerges at the intersection of transport disadvantage and social disadvantage (Lucas, 2012). It arises when inadequate transport options—such as high costs, unreliability, and high travel times—are overlaid on socioeconomic challenges such as low income, unemployment, or limited abilities. This compound disadvantage amplifies social inequality, as those already vulnerable due to financial, health, or physical constraints are further isolated by transport systems that fail to meet their needs.

Existing research has found strong evidence of a vicious cycle between labor market marginality and poverty and social isolation (Gallie et al., 2003), and acknowledged the role of transport in both social exclusion (Allen & Farber, 2020; Church et al., 2000; Currie et al., 2010; Lucas, 2012; Luz & Portugal, 2022; Yigitcanlar et al., 2019) and labor market outcomes (Bastiaanssen, 2012, 2020; Korsu & Wenglenski, 2010). This body of work underscores the potential of transport and land use policies to counter social isolation and break the cycle of economic and social marginalization by enhancing accessibility to various out-of-home activities.

However, despite this potential, there remains a significant gap in examining how transport disadvantage among the unemployed affects participation in activities beyond the labor market. This gap represents a critical area for further investigation, particularly within the field of TRSE, highlighting the need for comprehensive studies that delve into these interrelated social, economic, and transport marginalization aspects.

Addressing this literature gap, the present study aims to delve into the intricate interplay between transport disadvantage and social exclusion, particularly focusing on how transport limitations impact the variety of out-of-home activity participation among the unemployed. By exploring these under-researched areas, this study seeks to contribute a deeper understanding to the field of TRSE, shedding light on the nuanced challenges faced by different segments of the population, particularly the unemployed, in their daily mobility and social participation.

Unemployment is defined as the situation where individuals are without paid employment, yet are actively looking and available for work (CBS, 2024b). This definition reflects a certain level of labor market engagement, indicating that the individuals are not employed but are willing and able to work, differentiating them from other non-working segments of the population who may not be seeking employment or are not available for work.

Central to the understanding of transport disadvantage in this context is the use of transport accessibility and car availability as its two dimensions. Transport accessibility is quantified through the lens of the number of jobs accessible (based on a log-logistic travel time decay function) for three distinct modes: car, public transport, and bicycle. Job accessibility serves as a proxy for overall accessibility to essential services and opportunities. This two-dimensional approach aligns with the literature emphasizing the importance of spatiotemporal accessibility and mobility in determining an individual's transport-related abilities to engage in a broad spectrum of activities (Bantis & Haworth, 2020; Kamruzzaman et al., 2016; Yigitcanlar et al., 2019).

The inclusion of car availability serves as a critical factor that bridges the gap between theoretical and practical mobility capabilities. Studies highlighted in the literature review, such as those by Gao et al. (2022), Lucas (2012), and Mattioli (2021), underscore the significant role of car access in enhancing both spatial and temporal mobility. Due to the varied nature of car availability resulting from different combinations of car ownership, driver's license possession, and the number of cars in a household, it's crucial to consider these three facets comprehensively when evaluating car availability. By integrating the two dimensions of transport accessibility and car availability, this study addresses the nuanced ways in which transport disadvantage can manifest, particularly affecting the unemployed who may face compounded barriers to accessing out-of-home activities and participating fully in societal activities.

Another aspect that increases the complexity of this research is the heterogeneity of the unemployed population in terms of financial means and car ownership, a critical aspect to consider when discussing transport disadvantage and social inclusion. This heterogeneity suggests that the unemployed are not a homogeneous group facing uniform challenges. While some may struggle financially and in terms of transport means, others might still possess significant financial resources and own one or more cars. This diversity has profound implications for how we address issues related to transport disadvantage. It highlights the need to differentiate between various subgroups within the unemployed population to tailor policies and interventions effectively.

To account for the transport disadvantage heterogeneity among the unemployed population, segmentation based on accessibility and car availability is thus essential. This segmentation becomes particularly pertinent when examining individuals with low levels of accessibility and car availability. Considering the complex nature of measuring car availability—acknowledging the influences from various combinations of car ownership, driver's license possession, and the number of cars in a household—it becomes clear that any attempt to define low car availability a priori based on these indicators would lead to a significant oversimplification of the issue. Similarly, the challenge of defining low accessibility is complicated by the lack of universally accepted standards. Ryan & Martens (2023) have pointed out that the adoption of accessibility standards is rare, and efforts to establish such standards face significant obstacles.

In light of these complexities, the research approach examines the prevalent patterns of transport accessibility and car availability among the unemployed, rather than attempting to apply rigid definitions of low accessibility or car availability. This method enables a detailed examination that considers the varied situations within the unemployed population. By focusing on comparisons between these prevalent patterns, the study seeks to identify the specific ways in which differences in transport accessibility and car availability influence the ability of unemployed individuals to engage in out-of-home activities.

Moreover, it is pertinent to focus on the concept of out-of-home activity participation, which, although related, is not synonymous with social inclusion. Out-of-home activity participation refers to the engagement of individuals in activities outside of the home, a concept that is more directly impacted by transport disadvantage than social inclusion. Recognizing these nuances is vital for developing strategies that are not only inclusive but also effective in mitigating the specific transportation challenges faced by different segments of the unemployed population.

It is hypothesized that there exists a compensatory relationship between transport accessibility and car availability. High accessibility to essential services and activities via public transport, walking, or cycling could mitigate the impact of limited car availability. Conversely, individuals with high car availability may overcome the disadvantages of low accessibility in their residential area by traveling longer distances to access services and activities.

The TRSE-risk levels are thus predicated on the interplay between these two dimensions. Individuals with high accessibility and high car availability are presumed to be at the lowest risk of TRSE, as they have multiple options for engaging with society. Those with either high accessibility or high car availability are considered to be at a moderate risk of TRSE, as one dimension can compensate for shortcomings in the other.

However, the group presumed to face the highest risk of TRSE comprises unemployed individuals who experience both low accessibility and low car availability. For these individuals, the inability to access services and activities due to poor local infrastructure or service provision is compounded by a lack of car access. This double disadvantage presumably creates a significant barrier to participation in essential and discretionary out-of-home activities, which can lead to social exclusion.

1.1. Research formulation

Building on the recognition of the underexplored dynamics between transport disadvantage and the diverse activity participation of the unemployed, this study is designed to dissect these intricate interactions within the Netherlands.

The core objective of this research is to delineate the distinct patterns and consequences of transport disadvantage for the unemployed, focusing on two main dimensions—transport accessibility and car availability—which are supposedly compensatory. The study endeavors to clarify how constraints in these two areas impact the capacity of unemployed individuals to engage in out-of-home activities. This investigation aims to uncover potential strategies for policy intervention. By thoroughly examining these facets of transport disadvantage, the research seeks to contribute to a deeper comprehension of its wider societal effects and support the development of more inclusive approaches in transport and urban planning.

Research Objective

To investigate and elucidate the relationship between transport disadvantage and out-of-home activity participation among unemployed individuals in the Netherlands, to identify key patterns and insights that contribute to our understanding of transport-related social exclusion.

Guided by this objective, the main research question frames the core investigation.

Research Question Main

What are the prevalent patterns of transport accessibility and car availability among unemployed individuals in the Netherlands, and how do these patterns influence their participation in out-of-home activities?

To support this main question, two focused sub-questions have been formulated, both probing a specific facet of the overarching theme. The first sub-question aims to categorize and thoroughly understand the varied experiences of transport accessibility and car availability among the unemployed, explaining how these patterns correlate with the urbanization level of their living environment and are shaped by socio-demographic factors such as income, age, and education level. These factors are often indicative of broader social disadvantages. This comprehensive approach ensures a holistic understanding of the interplay between transport accessibility, car availability, urban settings, and socio-demographic factors, setting the stage for targeted and effective policy interventions to mitigate TRSE among the unemployed.

Research Question Main.1

What socio-demographically determined transport accessibility and car availability patterns, in which residential locations, exist among unemployed individuals in the Netherlands?

The second sub-question shifts focus to the behavioral impacts of transport disadvantage, as shaped by socio-demographic factors, on the participation in out-of-home activities, especially among the unemployed. In this segment, I explore how transport-related constraints affect engagement in these activities, considering the diverse socio-demographic and residential contexts uncovered in the first sub-question. This inquiry aims to quantify the extent to which transport limitations hinder the ability of unemployed individuals to partake in essential out-of-home activities, thereby deepening our understanding of the transport barriers to social inclusion.

Research Question Main.2

Which unemployed individuals, in which residential locations, face transport-related limitations in their out-of-home activity participation?

Together, these interlocking sub-questions construct a scaffold that supports the main research question. They enable a segmented yet cohesive analysis that aims to contribute a textured understanding of the factors that might lead to TRSE among the Netherlands' unemployed inhabitants. This thesis, through its methodical and targeted inquiries, aspires to offer actionable insights, informing policies that could mitigate the risks of social exclusion by improving access to essential services and opportunities.

1.2. Research conceptualization

The research conceptualization adopted in this study is strategically designed to forge a connection between the formulated research questions and the theoretical constructs depicted in the conceptual model diagram, see Figure 1.1. The conceptual model serves as a methodological bridge, linking the identification of socio-demographically determined transport disadvantage patterns and the subsequent impact on out-of-home activity participation among the unemployed. This entails an examination of how the presumed compensatory dimensions of transport accessibility and car availability influence out-of-home activity participation.

Figure 1.1 vividly illustrates the operationalization of the research questions. The first sub-question, which seeks to identify distinct socio-demographically determined transport accessibility and car availability patterns among the unemployed, corresponds with the 'Determinants' and 'Transport disadvantage patterns identification' segments of the conceptual model. Here, the determining nature of the socio-demographic factors regarding accessibility and car availability, and the interplay of these ostensibly compensatory dimensions of transport disadvantage against the backdrop of the hypothesized TRSE-risk is captured.

The socio-demographic profiles are constructed based on the factors of gender, age, household type and individual position, education level, standardized disposable household

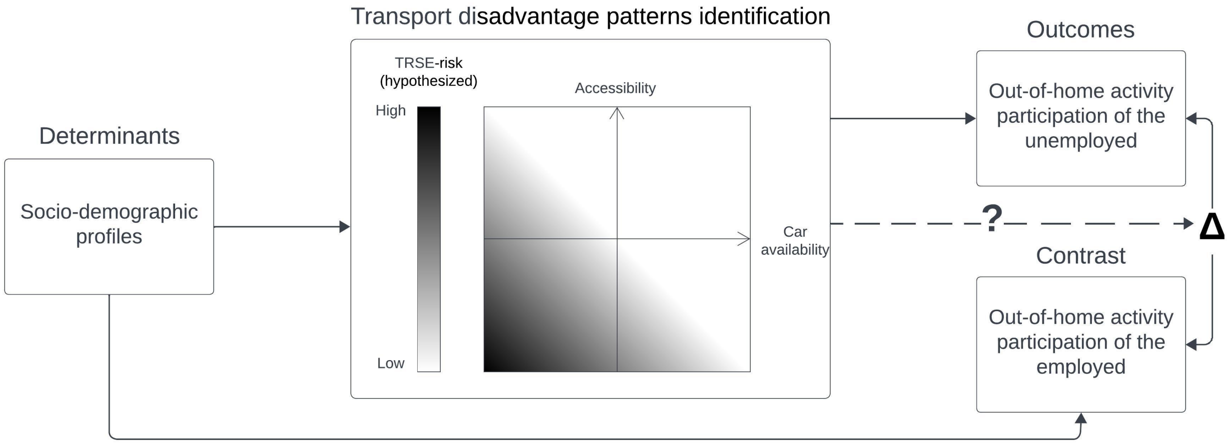


Figure 1.1: Conceptual model diagram.

income (adjusted to a one-person household), and (parental) birthplace. The investigation of these determinants and their influence on transport accessibility and car availability patterns aims to understand the underlying socio-demographic factors that shape transport disadvantage patterns.

The model further postulates that by contrasting the out-of-home activity participation of the various unemployed transport disadvantage groups with respective employed groups that share similar socio-demographic profiles, insights into limited out-of-home activity participation of the unemployed can be ascertained. This comparison is the first step to responding to the second sub-question and is crucial for identifying the specific activities that the unemployed are potentially excluded from.

The second and final step in answering the second sub-question involves comparing limited out-of-home activity participation among unemployed people classified within various socio-demographically determined accessibility and car availability segments. As such, this investigation will consider the gradient of TRSE-risk across different combinations of accessibility and car availability, providing a nuanced understanding of how these transport disadvantage patterns shape an unemployed individual's experience of transport-related limitations potentially indicative of TRSE.

1.3. Research approach

Latent class cluster analysis (LCCA) is exceptionally suited for identifying prevalent patterns of transport accessibility and car availability among the unemployed without predefined categories, due to its ability to uncover latent groups based on observed characteristics.

This method allows for the exploration of the complex and diverse nature of the unemployed population's transport disadvantage situations, accommodating the multifaceted aspects of transport accessibility and car availability.

By revealing data-driven insights into distinct clusters of individuals with similar transport disadvantage patterns, LCCA facilitates the development of nuanced and targeted transport and land use policy interventions. This approach avoids the oversimplification inherent in applying arbitrary definitions and sufficiency thresholds to the complex constructs of transport accessibility and car availability, ensuring that solutions are grounded in the actual experiences and needs of different segments of the unemployed population.

Other clustering methods, such as k-means clustering, do not offer the same level of suitability as LCCA for analyzing transport accessibility and car availability among the unemployed, primarily due to their reliance on predefining the number of clusters and the potential for substantial biases. These biases emerge when individuals do not neatly fit into one group, a common occurrence given the highly heterogeneous nature of transport disadvantage experiences. K-means clustering, for example, assumes homogeneity within clusters and equal variance across them, which can oversimplify the complexities inherent in the data.

In contrast, LCCA allows for the classification of individuals into clusters based on their probabilistic membership, accommodating the ambiguity and overlap that may exist among different segments of the unemployed population. This probabilistic approach reduces the biases associated with hard clustering methods and provides a more nuanced understanding of the diverse transport accessibility and car availability patterns present within the unemployed demographic.

The implementation of the conceptual model through LCCA utilizes accessibility indicators—the number of accessible jobs (based on a log-logistic travel time decay function) by car, public transport, and bicycle—to represent general accessibility through widely used modes. Car availability indicators are captured through measures reflecting car ownership, driver's license possession, and the number of cars in the household. The LCCA will categorize individuals into distinct groups based on these indicators while controlling for the aforementioned socio-demographic factors by including those factors as active covariates.

Out-of-home activity count by type is operationalized in the LCCA framework by including them as distal outcomes. These activities encompass commuting, business or occupational activities, shopping, transportation of people or goods, education, social visits, recreational activities, touring or hiking, services or personal care, and remaining activities. These counts provide a quantitative measure of participation in societal functions, which gives an indication of the extent of TRSE when contrasted with what may be considered socially included.

Hence, the contrast between the employed and unemployed is made. This contrast is established through propensity score matching, finding a similar socio-demographic profile of an employed counterpart for each unemployed person. This method allows for a quasi-experimental design, enabling the isolation of the combined effects of employment status and various patterns of transport accessibility and car availability on out-of-home activity participation.

It’s important to acknowledge that while patterns of transport accessibility and car availability are significantly influenced by socio-demographic determinants, substantial pattern heterogeneity may still exist within similar socio-demographic profiles. This heterogeneity arises because determinants beyond those captured by socio-demographic factors, such as transport and urban planning policies, also play a crucial role. Consequently, given that unemployed individuals are grouped primarily based on transport disadvantage patterns, and employed individuals are matched based solely on socio-demographic similarity, there can still be substantial differences in transport disadvantage patterns between these employment-status-differentiated groups.

It follows that the comparison between the out-of-home activity participation of the socio-demographically similar unemployed and employed enables the filtering of the (mostly transport-policy-wise immutable) direct socio-demographic influences on transport disadvantage from direct influences due to unemployment and non-socio-demographic factors.

Subsequently, the study compares out-of-home activity participation among different transport accessibility and car availability group patterns among the unemployed. This comparison is key in disentangling the intricate influence of transport disadvantage on activity participation from the influences attributable to employment status. This nuanced approach enhances our understanding of how transport accessibility and car availability interact with employment in shaping participation in out-of-home activities.

Through this rigorous analytical process, the thesis provides insights into the subtle yet significant ways in which transport disadvantage may adversely affect the social inclusion of the unemployed, providing a foundation for targeted transport and land use policy interventions.

2

Methodology

This study employs a carefully selected methodological approach, integrating a literature review, latent class cluster analysis (LCCA), propensity score matching, and the Wilcoxon signed-rank test, to explore the relationship between transport disadvantage and out-of-home activity participation among the unemployed in the Netherlands. This methodology is carefully chosen to align with the research objective of identifying distinct patterns of transport accessibility and car availability, and understanding their impact on out-of-home activity participation.

2.1. Literature review

The literature review undertakes a structured exploration, focusing on unraveling the complexities surrounding activity participation and transport disadvantage, especially within the context of economic disadvantage. Initially, it dissects factors pivotal in defining and measuring both activity participation and transport disadvantage. This examination ensures a foundational understanding that captures the diverse aspects of these phenomena, setting a critical baseline for appreciating the varied dimensions of transport disadvantage and the range of activities individuals engage in.

Hereafter, the review delves into interacting factors—ranging from socio-demographic elements to psychological and physical considerations—that might obscure the relationship between economic disadvantage, transport disadvantage, and activity participation. This segment of the review highlights the importance of accounting for these factors to accurately assess the impact of transport disadvantage on out-of-home activity participation among the unemployed.

Further, the review broadens its scope to encompass economic insights into TRSE across various global contexts. This comparative analysis sheds light on the unique challenges encountered by communities in both the global North and South, aiming to pinpoint economic TRSE considerations within the Netherlands while placing them within an international framework.

Converging in a comprehensive synthesis, the literature review aims to spotlight a significant research gap. It sets the stage for an inquiry into how employment status combined with transport disadvantage influences out-of-home activity participation, paving the way for research interventions that could mitigate the cycle of social and economic marginalization.

The literature search endeavor started with a broad array of sources that were narrowed down through an iterative search and selection process. Initial searches through the academic databases of Scopus and Google Scholar laid the groundwork, combining terms related to transport disadvantage, social exclusion, and economic disadvantage to capture a wide spectrum of relevant research. From the initial pool of 252 findings, studies were meticulously chosen based on their direct relevance to the main research question.

To deepen the literature exploration and ensure a thorough grasp of the subject matter, the snowball method was employed. This technique, leveraging the interconnected nature of scholarly work, allowed for the expansion of the literature base by tracing the references within initially identified papers to uncover further pertinent studies. Similarly, papers citing the foundational studies were examined for additional insights. This snowballing process enriched the review, enabling the incorporation of a diverse range of perspectives and findings.

2.2. Latent class cluster analysis

LCCA is central to this study, as it facilitates the identification of distinct transport accessibility and car availability patterns among the unemployed. LCCA operates on the principle that a discrete, unobserved variable is capable of accounting for the connections among a set of observable indicators. This principle, known as 'local independence,' suggests that the associations among these indicators become insignificant when the latent variable is controlled for (McCutcheon, 1987; Vermunt & Magidson, 2004). The essence of employing LCCA is to identify the simplest model that adequately describes the data. This simplicity is quantified by the number of latent classes that the model contains.

Distinguishing LCCA from latent class choice models (LCCMs) is crucial, as they both utilize a latent variable but differ in application and structure. LCCMs are primarily concerned with capturing diversity in preferences or choices that are influenced by a range of explanatory variables.

On the other hand, LCCA assumes that the latent variable directly informs the outcomes of the indicators. This assumption aligns LCCA more closely with factor analysis, where the focus is on understanding the variance in indicators. LCCA, therefore, groups entities based on indicator pattern differences, not on how various variables affect choices (Molin et al., 2016).

2.2.1. Motivation

The motivation for employing LCCA in this thesis stems from the need to discern distinct patterns of transport accessibility and car availability among unemployed individuals without imposing arbitrary definitions. This statistical method facilitates a sophisticated exploration of how socio-demographic characteristics interplay with transport disadvantage variables to affect out-of-home activity participation.

LCCA has been successfully applied in various transportation studies to identify unique groups based on travel behaviors and preferences. Notable studies utilizing LCCA in transportation include those by Goulias et al. (2003), who identified groups of solitary travelers and those that travel together; Goulias & Henson (2006), who distinguished altruists from egoists in terms of travel and activity participation; Deutsch & Goulias (2013), who analyzed social network types; Kim et al. (2005), who categorized travelers based on diary-reported mode usage; Beckman & Goulias (2008), who explored immigrant travel behaviors; Bamberg (2013), who looked into car use behavioral changes; and Depaire et al. (2008), Kaplan & Prato (2013), and de Oña et al. (2013), who applied LCCA to classify road accident injury severity.

In the context of this study, LCCA's efficacy is evidenced by Molin et al. (2016), who group Dutch travelers based on their frequency of transport (multi-)mode use, using socio-demographic, mode perceptions, and attitudinal variables as covariates. The study highlights LCCA's capacity for reducing misclassification biases by probabilistically assigning individuals to clusters, which is crucial given the approximate nature of the transport accessibility and car availability indicators used in this research. Additionally, LCCA's unique ability among clustering techniques to use statistical criteria to determine the optimal number of clusters and handle mixed-scale variables directly applies to my study, especially considering the mixed-scale nature of my indicators, like ordinal car ownership and continuous transport accessibility measures.

Further justification for the use of LCCA comes from Anowar et al. (2014), who demonstrated how car access patterns correlate with urbanization levels, echoing my investigation into the connection between urbanization, car availability, and accessibility. Their approach to capturing systematic heterogeneity and providing intuitive interpretations of transport behaviors reinforces the decision to apply LCCA to dissect the transport disadvantage experienced by unemployed individuals across different urban settings.

Lastly, similar to Hyun et al. (2022), who identified distinct travel behavior patterns among older adults, this thesis utilizes LCCA to unearth the underlying socio-demographic and transport-related factors that govern the travel behaviors of unemployed individuals. By adapting this method, the study not only aligns with the precedent set by prior research but also avoids imposing arbitrary thresholds for low accessibility and car availability.

2.2.2. Structure

As illustrated in Figure 2.1, the indicators in this study's LCCA model encompass transport disadvantage, including car and public transport accessibility, bike accessibility, car availability, and household car ownership. They are chosen for their direct impact on individual car availability and their relevance in reflecting the transport infrastructure's adequacy in accommodating various travel needs. Specifically, accessibility indicators, reflecting the general level of access to destinations, are proxied by the number of accessible jobs (based on a log-logistic travel time decay function). Car availability indicators consist of three measures: car ownership, driver's license possession, and the number of cars in a household.

The covariates in Figure 2.1 are divided into active and inactive types. Active covariates include socio-demographic variables such as age, income, and education level. These are used actively in the LCCA model to influence the formation of latent classes, reflecting the structural socio-demographic impact on transport disadvantage and, consequently, travel behavior. Inactive covariates—specifically residential location variables such as urbanization level and postal code—are used to offer contextual insights into the latent classes without influencing their formation.

The distal outcomes featured in Figure 2.1 represent the consequential travel behaviors of interest. They include the out-of-home activity count by type, mode usage, travel period, and total travel distance and time. These outcomes are not directly involved in the clustering process but are critical for understanding the impact of the latent classes on actual travel behavior. They help to appreciate the practical implications of transport disadvantage on

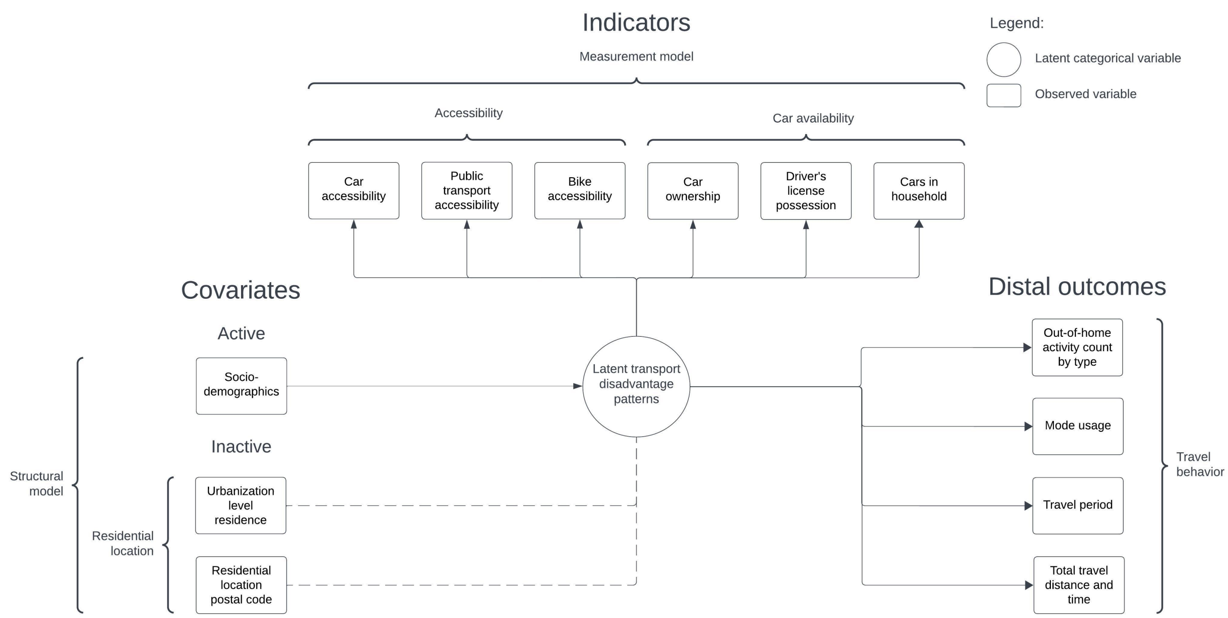


Figure 2.1: Latent class cluster model with covariates and distal outcomes graphical representation.

the out-of-home activity participation and travel behavior of the unemployed.

2.2.3. Mathematical model

For the set of indicators $y = \{y_1, y_2, \ldots, y_J\}$, encompassing the transport accessibility and car availability measures of transport disadvantage, the latent transport disadvantage categorical variable z, shaped by a vector of socio-demographic covariates x, segments the population into K latent classes. The model's foundation lies in the probability of an individual's indicator pattern y, given by:

$$P(y \mid x) = \sum_{k=1}^{K} P(z = k \mid x) \prod_{j=1}^{J} P\left(y_j \mid z = k\right), \tag{2.1}$$

with the local independence assumption that the transport disadvantage indicator pattern is solely a manifestation of the latent categorical z, thus the various patterns in y are independent, conditional on z.

The class membership probability follows a multinomial logistic regression where socio-demographic covariates x are predictors for class membership z:

$$P(z = k \mid x) = \frac{\exp\left(\beta_{0k} + \beta_k^T x\right)}{\sum_{l=1}^{K} \exp\left(\beta_{0l} + \beta_l^T x\right)}, \tag{2.2}$$

with β_{0k} as the intercept and β_k as the vector of coefficients related to socio-demographic covariates x. Due to limitations in the software used for implementation, the socio-demographic covariates x are all modeled as nominal variables despite the existing ordinal structure in age, education level, and standardized disposable household income group.

The mathematical formulation of the probabilities of particular transport disadvantage patterns of the indicator variables given latent class membership depends on the measurement scale of the indicator. The indicator pattern probability of the continuous transport accessibility indicators for car, public transport, and bike are modeled using a normal distribution:

$$P\left(y_j^c \mid z=k\right)=\mathcal{N}\left(y_j^c;\alpha_j+\zeta_{jk},\sigma^2\right), \tag{2.3}$$

with α_j as the overall mean across classes for indicator j and ζ_{jk} as the class-specific adjustment to the mean for class k. The cluster-independent variance σ^2 is not directly specified but a standard normal distribution is assumed for the underlying latent variable or factor (Vermunt & Magidson, 2005b).

For the car ownership or driver's license possession binary indicator y_j^b with two possible outcomes, the logistic regression for the probability of category c within latent class k is given by:

$$P\left(y_j^b=c \mid z=k\right)=\frac{\exp\left(\gamma_{jc}+\delta_{jk}\right)}{1+\exp\left(\gamma_{jc}+\delta_{jk}\right)}, \tag{2.4}$$

where γ_{jc} represents the log-odds of the outcome for category c across all classes for indicator j, and δ_{jk} is the adjustment to the log-odds for class k.

The number of cars in a household is represented by the ordinal indicator y_j^o, with the set of ordered categories $m=\{0,1,2^+\}$ modeled as $m=\{0,1,2\}$. The ordinal logistic regression accounts for each level increment proportionally. The probability of observing an ordinal outcome at level m is modeled as:

$$P\left(y_j^o=m \mid z=k\right)=\frac{\exp\left(\eta_{jm}+\tau_{jk}\cdot m\right)}{\sum_{m'=1}^{M}\exp\left(\eta_{jm'}+\tau_{jk}\cdot m'\right)}, \tag{2.5}$$

where η_{jm} provides the log-odds for level m of the ordinal response for indicator j, and τ_{jk} reflects the incremental effect associated with each step up in the level m for class k.

To accurately estimate the association between latent class membership and the distal outcomes of out-of-home activity participation and travel behavior, a bias-adjusted three-step method (Bakk et al., 2013) is employed. This method corrects for classification errors in the assignment of individuals to latent classes, thereby enhancing the validity of the subsequent association analysis. Distal outcomes, specifically travel distance and travel time, are presumed to follow a normal probability distribution, reflecting the continuous nature of these measures, analogous to the modeling of continuous transport accessibility indicators. In contrast, for the remaining distal outcomes pertaining to out-of-home activity participation and travel behavior, which are count data, a Poisson probability distribution is utilized, effectively capturing the discrete and non-negative characteristics of these variables.

2.3. Propensity score matching

Propensity score matching plays a crucial role in this study, enabling a nuanced comparison between the employed and unemployed who share similar socio-demographic profiles. This comparison is key to understanding the specific out-of-home activities where different socio-demographically determined transport accessibility and car availability groups of the unemployed exhibit significantly lower levels of participation compared to their employed counterparts.

The foundation of propensity score matching lies in its ability to reduce selection bias by equating groups based on propensity scores, which are the probabilities of assignment to a particular treatment given a set of observed covariates (Rosenbaum & Rubin, 1983). These scores are derived through logistic regression, balancing the distribution of observed covariates between the treatment (unemployed) and control (employed) groups, reducing selection bias, and simulating the conditions of a randomized experiment. The propensity score—essentially the probability of an individual being unemployed given their socio-demographic characteristics—is computed for each person in the study. Individuals from the unemployed group are then matched with those from the employed group who have similar propensity scores, ensuring that the comparison of out-of-home activity participation is made between unemployed and employed groups that are socio-demographically equivalent, yet may differ in terms of transport accessibility and car availability.

2.3.1. Motivation

The choice to employ propensity score matching in this study is fundamentally driven by the need to create a balanced observational comparison that mimics the conditions of a randomized experiment, which is inherently impossible with the cross-sectional travel diary data available. This technique is instrumental in creating a quasi-experimental setting from observational data, where true random assignment to treatment and control groups is infeasible. Propensity score matching addresses this by simulating randomization, thus enabling more reliable causal inferences about the combined impact of employment status and transport disadvantage on out-of-home activity participation.

The use of propensity score matching in this research aligns with prior studies such as those by X. J. Cao et al. (2010) and X. Cao & Fan (2012), where propensity score matching was utilized to control for self-selection in assessing the impact of residential location on vehicle miles driven and urban density on car and transit travel duration, respectively.

The application of propensity score matching to the present study is further justified by its proven efficacy in studies such as Nasri et al. (2020), which estimated the effect of living in transit-oriented development areas on non-auto mode share, after controlling for residential self-selection bias. The precedents highlight the method's robustness in drawing reliable causal inferences about the aggregate impact of employment status and transport disadvantage on out-of-home activity participation.

Acknowledging the limitations inherent in propensity score matching, this thesis adopts a rigorous approach to enhance the reliability of its findings. Given that propensity score matching operates under the assumption that all relevant confounders must be observed, an extensive variable selection process was conducted. This process involved carefully curating a comprehensive set of socio-demographic variables known to influence both employment status and out-of-home activity participation. This meticulous selection is designed to ensure that the matching process adequately controls for potential confounders, thereby strengthening the validity of the causal inferences drawn from the analysis.

The integration of clustering methods with propensity score matching, as demonstrated by Park et al. (2018) and Deng & Yan (2019), showcases a powerful approach to uncovering the built environment's effects on travel behavior. These studies illustrate the effectiveness of combining clustering to identify distinct patterns with propensity score matching for rigorous comparisons, thereby reinforcing the methodological underpinning of this study.

In conclusion, while propensity score matching has its limitations, particularly in its reliance on observed variables, the method's application in this study is justified given the data constraints and the research objectives.

2.3.2. Structure

The structure of the propensity score matching analysis conducted in this study is visually summarized in Figure 2.2, which provides a graphical representation of the matching process between unemployed and employed individuals based on socio-demographic characteristics. In the initial phase, the propensity scores for each individual are calculated using logistic regression, to match the 1,840 unemployed individuals to a significantly larger group of 51,793 employed individuals.

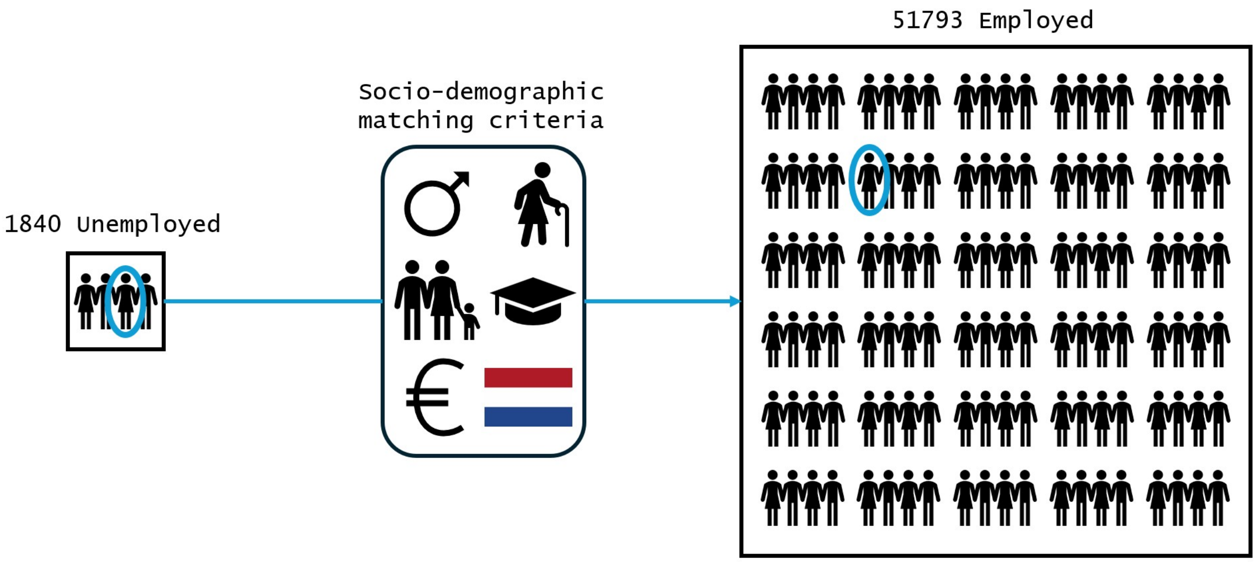


Figure 2.2: Propensity score matching of unemployed to socio-demographically similar employed graphical representation.

The socio-demographic matching criteria—gender, age, household type and individual position, education level, standardized disposable household income group, and parental birthplace—are illustrated through specific icons in the graphic, signifying their role as covariates in the logistic regression model. These criteria consist of the exact same variables as the active covariates in the LCCA model, that are presumed to influence the latent transportation accessibility and car availability patterns.

Once propensity scores are calculated, matching is performed to align each unemployed participant with an employed individual who has the closest propensity score, as shown by the blue arrow in Figure 2.2. In this matching, an employed individual is matched to only one unemployed participant, ensuring that no employed individual is paired with more than one unemployed counterpart. This approach ensures a one-to-one comparison, facilitating an accurate assessment of activity participation between groups that are similar in socio-demographic characteristics but may differ in their experiences of transport accessibility and car availability.

The resulting matched dataset thus comprises pairs of unemployed and employed individuals who share equivalent propensity scores, offering a balanced framework to assess the combined effect of employment status and transport disadvantage on out-of-home activity participation. This matching process, as illustrated, is a critical step toward achieving the study's goal of understanding the nuanced relationships between employment status, transport disadvantage, and activity participation.

Following the completion of the matching procedure, the matched pairs are then subjected to further analysis to evaluate the disparity in out-of-home activities, with a keen focus on examining how employment status interplays with transport disadvantages.

2.3.3. Mathematical model

The mathematical model for the propensity score is delineated by the probability of an individual being unemployed (treatment) conditioned on the observed socio-demographic covariates. The propensity score $p(X)$ is modeled using a logistic regression as follows:

$$p(X) = P(T = 1 \mid X), \tag{2.6}$$

where T represents the treatment assignment (1 for unemployed and 0 for employed) and X encapsulates the covariates: gender, age, household type and individual position, education level, standardized disposable household income, and parental birthplace. The logistic regression model can be formalized as:

$$\log\left(\frac{p(X)}{1 - p(X)}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_6 X_6, \tag{2.7}$$

where β_0 is the intercept and each of the other β coefficients represents the coefficient associated with one of the six socio-demographic covariates.

Post propensity score estimation, nearest-neighbor matching without replacement is conducted, ensuring that each unemployed individual is matched to one employed individual with a similar propensity score. The matching process is weighed by personal level weights, normalized using Min-Max normalization, to maintain balance in the influence of each observation.

Upon obtaining the matched dataset, the study moves to the impact analysis phase, where the effects of employment status and transport disadvantage on out-of-home activity participation and travel behavior are scrutinized. The impact analysis is underpinned by the Wilcoxon Signed Rank Test—a non-parametric statistical test suitable for paired data.

2.4. Wilcoxon signed-rank test

Following the propensity score matching process, I implement the Wilcoxon signed-rank test to conduct a pairwise comparison of matched unemployed and employed individuals with respect to various outcome variables concerning activity participation and travel behavior. This non-parametric statistical test is an appropriate choice, especially considering that the distribution of the differences for count data, which includes many zeros leading to zero-inflation, likely deviates from normality. Such deviation from normality means that a more conventional paired sample t-test, which assumes normality of the differences between pairs, is not suitable for my data. The Wilcoxon signed-rank test, by not requiring the differences to follow a normal distribution, allows for a more accurate assessment of median differences between the groups in the presence of zero-inflated and skewed data.

For a matched pair i, let $x_{i,1}$ represent an outcome variable for the unemployed individual and $x_{i,2}$ for the employed counterpart. I calculate the differences $d_i = x_{i,1} - x_{i,2}$ for all n pairs in the sample. Each non-zero difference $|d_i|$ is ranked from 1 to n, with tied differences receiving a rank equal to the average of their positions in the ascending order of the absolute differences.

The Wilcoxon signed-rank test statistic W is computed as the sum of the signed ranks:

$$W = \sum_{i=1}^{n} \operatorname{sgn}(d_i) \times R(|d_i|), \tag{2.8}$$

where $\operatorname{sgn}(d_i)$ is the sign function that assigns a value of 1, 0, or -1 depending on whether d_i is positive, zero, or negative, respectively, and $R(|d_i|)$ is the rank of the absolute difference $|d_i|$.

The null hypothesis H_0 of the test posits that the set of pairwise differences between the outcomes of the unemployed and employed individuals has a probability distribution centered at zero. The calculated test statistic W is compared against the Wilcoxon distribution to determine whether to reject H_0. A significant W would indicate an overall difference in the outcomes between the matched pairs.

In addition to the test statistic W and its p-value, I calculate the mean of the differences d_i, which functions as a singular numeric measure of the average excess or shortfall in activity participation and travel behavior outcomes for the unemployed compared to their employed counterparts.

Mean differences provide an accurate picture because mean differences quantify the average effect across all matched pairs, providing insight into the overall magnitude of the impact of unemployment on out-of-home activity participation for various transport disadvantage groups. This is particularly relevant in the context of zero-inflated data, where the presence of a large number of zeroes can mask significant variations in the non-zero data points. By focusing on the mean, I can capture the full extent of these variations, including both the direction and magnitude of the effect.

In my analysis, the Wilcoxon signed-rank test is applied to each transport disadvantage cluster separately. This strategy accounts for cluster-specific variations and confirms that the findings reflect the impact of transport disadvantage and employment status on out-of-home activity participation.

I interpret the test results, including the mean excess and p-values of the Wilcoxon signed-rank test statistic, to understand the magnitude, direction, and significance of the impact of employment status and various transport disadvantage patterns on out-of-home activity participation. These results are essential to my thesis, as they aid in addressing the central research question of how transport disadvantage shapes the out-of-home activity participation of the unemployed in the Netherlands.

3

Literature review

This chapter delves into the literature concerning aspects of TRSE, specifically in connection with economic disadvantage, to a certain extent guided by the incisive framework presented in Lucas (2012). Figure 3.1 serves as a conceptual map, illustrating the intricate interconnections between transport disadvantage, social disadvantage, and social exclusion within the broader context of social norms, economic structures, and governance frameworks. The light gray shaded area in the diagram specifically highlights the focus of the study: economic disadvantage, transport disadvantage, and social exclusion. By dissecting certain elements of this diagram, this chapter seeks to unravel the complex layers of economic disadvantage's link to TRSE.

A pivotal aspect to be accounted for in all facets of economic disadvantage, transport disadvantage, and social exclusion is the relativity perspective, a perspective emphasized by Lucas (2012) and Kenyon et al. (2002). This relativity approach involves comparing economic disadvantage, transport disadvantage, and social exclusion levels of individuals or groups within a specific area. It acknowledges the diverse impacts of TRSE in high-mobility societies, where increased mobility requirements amplify disparities in transport access and social participation.

This literature review is structured as follows. First, factors critical in defining and measuring both activity participation and transport disadvantage are examined. Subsequently, interacting factors are discussed that, if not accounted for, might distort the connections between economic disadvantage, transport disadvantage, and activity participation. Afterward, this literature review treats economic TRSE insights from studies in a wide variety of geographical contexts. This literature review culminates in a synthesis that not only highlights the research gap this study intends to fill but also integrates key findings and

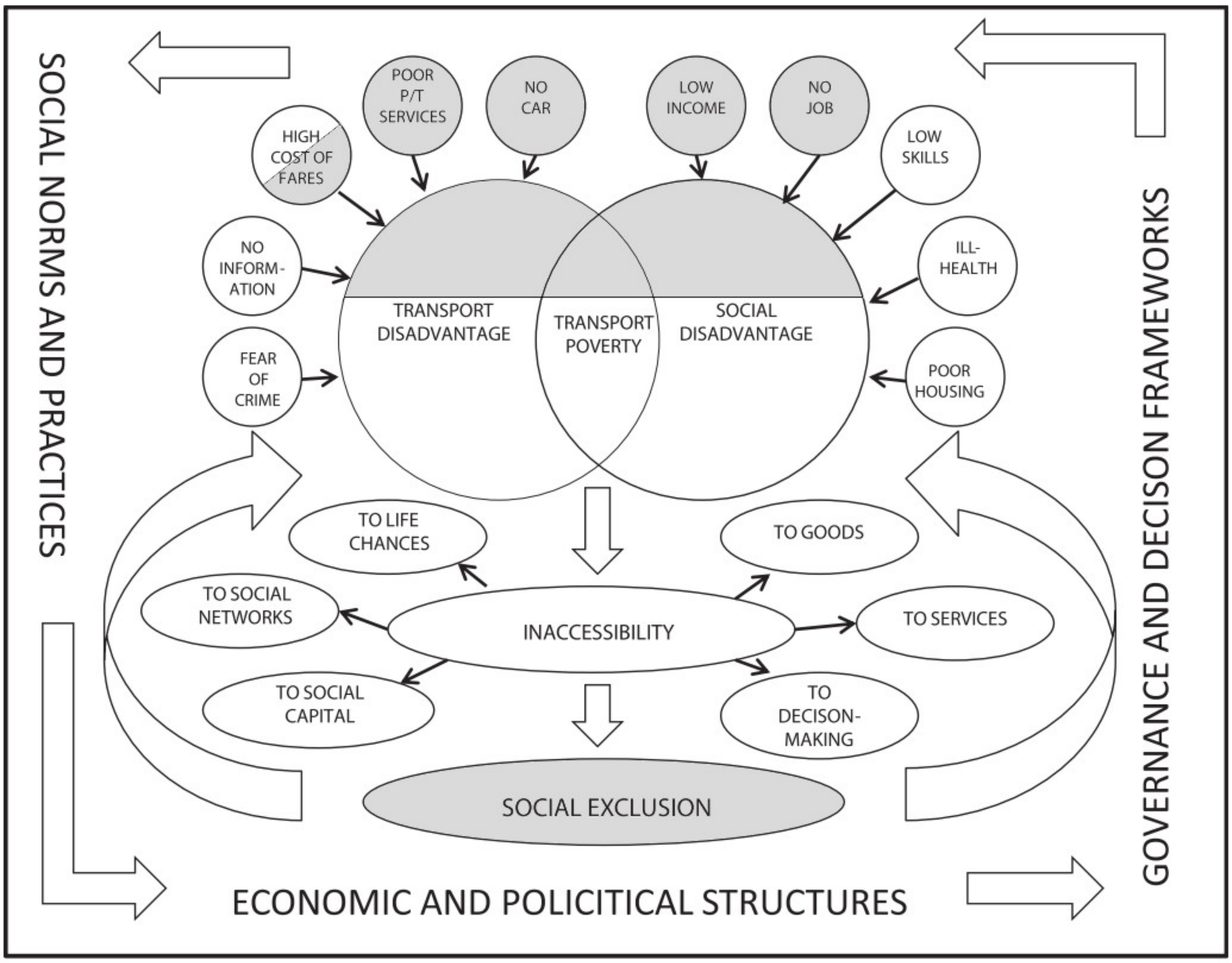


Figure 3.1: Diagram to illustrate the relationship between transport disadvantage, social disadvantage, and social exclusion.

Note: The light gray shaded area depicts the economic TRSE focus of this study (adapted from Lucas, 2012).

insights from the entire literature review.

3.1. Activity participation

In assessing the concept of activity participation in relation to transport disadvantage, it is essential to distinguish between transport disadvantage and transport-related exclusion from activities. These concepts are not inherently equivalent, as highlighted by Currie & Delbosc (2010). An individual might possess sufficient transport means yet still encounter barriers to participating in activities, or they might be actively involved in societal activities despite facing transport-related challenges.

Kamruzzaman et al. (2016) emphasize the necessity of employing multidimensional indicators for a comprehensive understanding of activity participation. These indicators should encompass various aspects such as the count, type, frequency, and duration of activities engaged in by individuals. This approach is crucial for accurately assessing the extent to which individuals are participating in societal activities. They argue that a singular indicator is insufficient for effectively capturing evidence of an individual's risk of exclusion due to reduced activity participation. Consequently, a unique methodology is required for measuring activity participation, combining various dimensions of indicators that assess participation outcomes.

3.2. Transport disadvantage

In assessing transport disadvantage, four pivotal factors are considered. The first is the spatial accessibility dimension; Bantis & Haworth (2020), Bastiaanssen & Breedijk (2022), and Martens & Bastiaanssen (2019) emphasize the need to consider factors such as distance to amenities and the spatial distribution of opportunities. This perspective acknowledges that spatial factors play a significant role in determining accessibility and, by extension, may impact social inclusion.

Temporal accessibility, specifically assessing the temporal availability and variation of opportunities and services, is crucial in measuring transport disadvantage (Kamruzzaman et al., 2016). By considering the dimension of temporal accessibility, transport disadvantage measurements can capture the dynamic nature of individuals' access to activities over time, recognizing variations in accessibility levels and constraints during different time periods (Yigitcanlar et al., 2019).

Spatial and temporal mobility also emerge as important factors and encompass the accessibility and availability of diverse transportation modes across geographical locations and over time (Kamruzzaman et al., 2016). Spatial mobility reflects individuals' access to transportation networks, services, and facilities within the spatial dimension. On the other hand, temporal mobility pertains to the availability, frequency, and travel time of transportation options, addressing individuals' temporal accessibility to engage in activities and participate in social and economic life.

The overarching determinant of transport disadvantage is often stated to be car access, as demonstrated in studies by Gao et al. (2022), Lucas (2012), Martens et al. (2019), and Mattioli (2021). Particularly in less urbanized areas, having access to a car markedly influences all other aspects of transport disadvantage. It underscores a critical dimension in ensuring high levels of spatial and temporal accessibility and mobility. This reality positions car access as a central determinant in the broader context of TRSE, impacting the ability to participate in various social and economic activities effectively.

3.3. Interacting social disadvantage factors

To fully comprehend the intricate connections between economic disadvantage, transport disadvantage, and activity participation, it is essential to consider the array of interacting social disadvantage factors that may influence these relationships. This discussion is not just limited to socio-economic and spatial variables; instead, it extends to a broader spectrum encompassing psychological aspects, physical abilities, information accessibility, discrimination, and socio-demographic elements. These factors collectively play a crucial role in shaping an individual's experience with transport systems and their social inclusion or exclusion.

Studies outside the transport domain emphasize the socio-demographic factors influencing the interplay between unemployment and social participation. Pohlan (2019) identifies heightened social exclusion risks among unemployed men, those with lower educational achievements, and individuals without supportive partnerships, with prolonged unemployment further weakening social ties. Kunze & Suppa (2017) discuss how unemployment impacts social engagement through income loss and increased leisure time, which can decrease or increase participation, respectively. They note the role of social norms and the potential for stigma to drive the unemployed away from public activities, suggesting that over time, the unemployed adjust their social behavior, possibly increasing activities like volunteering as substitutes for employment. Dieckhoff & Gash (2015) support these findings, showing that lower education and poor health correlate with reduced social engagement and that age influences the type of social participation, with older individuals favoring formal activities and younger ones preferring informal interactions.

Kamruzzaman et al. (2016) enrich the discussion on interactions by highlighting that within the context of TRSE, the interplay among socio-demographic factors, spatial context, and activity participation needs is critical for understanding the complex impacts on an individual's transport disadvantage and social inclusion. Specifically, the TRSE framework's ability to model interactions among socio-demographic variables such as age, household size, household composition, and education level with an individual's transportation needs and the spatial distribution of essential facilities and opportunities provides nuanced insights. This approach allows for a deeper understanding of the unique challenges faced by various socio-demographic groups in accessing activities and services, thereby contributing significantly to the discourse on transport disadvantage and social inclusion (Kamruzzaman et al., 2016).

Psychological factors or fear-based exclusion also play a crucial role in TRSE and may covary with economic disadvantage and social exclusion, potentially obscuring the connection between transport disadvantage and out-of-home activity participation among the unemployed. Casas & Delmelle (2014), Lättman et al. (2016), and Yigitcanlar et al. (2019) stress the importance of considering psychological dimensions like the conduct of others, security, and safety in using various transport modes.

Furthermore, Church et al. (2000) delineate the concept of physical exclusion within the context of TRSE, emphasizing various factors contributing to such barriers. They underscore the significance of physical exclusion by identifying specific features of the transport system that are contributing to or associated with the exclusion of certain population groups. These features encompass physical barriers, such as vehicle design and inadequate facilities for persons with disabilities.

Information exclusion is another relevant factor and refers to the lack of accessible information on public transport and destination options that prevent individuals from planning their journey and limit its use. This is often evidenced by the absence of travel information at transit stops, lack of information about the location of transit stops, and lack of information about service interruptions. Additionally, research indicates that the lack of digital connection or inability to use appropriate information and communication technology (ICT) may contribute to informational exclusion, further restricting access to transportation options and hindering full participation in society (Lättman et al., 2016; Yigitcanlar et al., 2019).

More recently, the concept of social position-based or discrimination-based exclusion has been extensively explored by Benevenuto & Caulfield (2019). It encompasses the prevention of individuals from moving into public spaces due to censure, social control, or other restrictions based on social attributes such as gender, national identity, race, ethnicity, religion, and more. Benevenuto & Caulfield (2019) draw attention to remarkable historical examples, ranging from the segregation policies observed in South Africa during the early ’90s to the prohibition on women’s driving in Saudi Arabia until 2018, thereby highlighting the lasting impact of historical cases on individuals’ access to public and private spaces. Furthermore, the paper illustrates how issues related to social position-based exclusion persist in various forms globally, reinforcing the need for comprehensive research and interventions to address these complex dynamics in the context of TRSE.

3.4. Economic transport-related social exclusion

Numerous studies in the field of TRSE have highlighted the role of poverty, low income, and unemployment as critical barriers to accessing essential destinations (Benevenuto & Caulfield, 2019; Currie & Stanley, 2007; Lucas, 2011; Ma et al., 2018). Individuals or social groups with economic disadvantages often face challenges in accessing transportation options that are not only affordable and reliable but also provide acceptable travel times, ensuring timely access to essential services and employment opportunities. Limited financial resources can restrict their mobility and access to essential services, contributing to social exclusion by hindering their participation in economic, social, and cultural activities (Wang et al., 2020).

In this section, I delve into the overlaps among economic disadvantage, transport disadvantage, and social exclusion. This triad is influenced by a confluence of interacting factors—as discussed in Section 3.3—and thus manifests differently across various regions. Recognizing the heterogeneity of these relationships is crucial for a nuanced understanding of the broader phenomenon.

My literature selection strategically encapsulates a diverse range of studies that significantly contribute to framing my research, allowing me to draw inferences on the generalizability of my findings. I focus on works that provide unique perspectives, such as balancing studies with an urban and rural context. Although I emphasize studies from Europe due to their relevance to my area of interest, this literature review extends to other regions—Australia, North America, South America, south and east Asia, and sub-Saharan Africa—drawing a more global picture of the interplay between economic disadvantage, transport disadvantage, and social exclusion. By examining these different settings, the review enhances our understanding of global patterns and regional variations, shedding light on both universal and unique aspects of transport-related limitations to out-of-home activity participation among the unemployed in the Netherlands.

In Australia, studies by Currie et al. (2010) and Dodson et al. (2010) reveal how transport disadvantage manifests as both reliance on others and limitations in public transport accessibility, affecting well-being and social exclusion, particularly under economic constraints such as low income and unemployment.

North America offers a range of perspectives where studies like Allen & Farber (2020), Conroy-Dalton (2007), Hu (2017), Paez et al. (2009), Sanchez et al. (2004), Ward & Walsh (2023), and Yousefzadeh Barri et al. (2023) underscore the importance of accessible, flexible, and affordable transportation options in mitigating social exclusion. These studies highlight the critical role of cars in enabling activity participation, particularly outside of major public transport corridors in urban areas and among economically disadvantaged communities where public transport may be absent or does not meet mobility needs.

European research, with contributions from Bastiaanssen (2012, 2020), Cebollada (2009), Cordera et al. (2017), Eichenauer (2023), Hine & Mitchell (2017), Kamruzzaman & Hine (2012), Lucas et al. (2016), Meert et al. (2003), SEU (2003), and van Dülmen et al. (2022), delves into the consequences of car-centric urban planning on employment access. These studies highlight that car availability profoundly influences job access disparities, particularly affecting low-income populations who suffer from both low car availability and inadequate public transport options. Such conditions significantly elevate the risk of social exclusion for these vulnerable groups, underlining the need for inclusive transport policies that accommodate diverse mobility needs.

In contrast, studies from the Global South highlight distinct challenges. In South America, research by Luz et al. (2022), Slovic et al. (2019), and Ureta (2008) notes how limited mobility due to poor transportation infrastructure restricts access to jobs and social networks, intensifying social exclusion. Specifically, the analysis by Ureta (2008) in Santiago, Chile, highlights how residential segregation coupled with inadequate transportation infrastructure contributes to social exclusion.

In sub-Saharan Africa, the research of Lucas (2011), Olvera et al. (2003), and Salon & Gulyani (2010) highlight the challenges posed by unplanned urban expansion and the increasing dependence on private transport providers. These factors have contributed to significant social and urban segregation. As a result, the absence of affordable motorized transport compels many to rely on walking, which in turn restricts their access to employment and social services. This limitation further entrenches social exclusion, underscoring the critical link between transport availability and social equity.

In south and east Asia, transportation challenges and social exclusion often follow a consistent pattern. For example, in Nanjing, China, Wang et al. (2020) notes that low-income residents have reduced access to public transit due to suburban relocations enforced by housing policies, which increases their risk of social exclusion. This scenario is echoed across the region, as studies by Cheng et al. (2019), Gao et al. (2022), Hickman et al. (2017), Pan & He (2023), and Tao et al. (2020) reveal. Economic limitations frequently restrict the mobility of low-income groups, affecting their car availability and access to other transportation modes. Consequently, this restricts their social inclusion and access to employment opportunities, underscoring a widespread issue across south and east Asia.

The differences between the Global North and Global South lie in the specific manifestations of transport disadvantage and social exclusion, influenced by diverse socio-economic and infrastructural contexts. While the Global North grapples with issues of affordability, accessibility, and the pivotal role of cars, the Global South faces a broader range of challenges, from the reliance on walking in sub-Saharan Africa to the impacts of urban planning and infrastructure quality in south and east Asia and South America. In both contexts, addressing economic disadvantage and improving accessibility to vital services and opportunities through affordable and reliable transportation options or urban planning are crucial in mitigating transport disadvantage and reducing social exclusion among the economically disadvantaged.

3.5. Synthesis and identification of research gap

This synthesis integrates key findings and insights from the literature review, laying the groundwork for identifying the research gap this study intends to fill. The review underscores the importance of multidimensional indicators for comprehensively understanding activity participation, which includes the count, type, frequency, and duration of activities individuals engage in (Kamruzzaman et al., 2016). Similarly, transport disadvantage is delineated by spatio-temporal accessibility and mobility, with car access identified as a pivotal determinant in the global North (Bantis & Haworth, 2020; Bastiaanssen & Breedijk, 2022; Gao et al., 2022; Kamruzzaman et al., 2016; Lucas, 2012; Martens & Bastiaanssen, 2019; Martens et al., 2019; Mattioli, 2021; Yigitcanlar et al., 2019).

Furthermore, the literature review highlights several interacting social disadvantage factors that, if overlooked, may obscure the connections between economic disadvantage, transport disadvantage, and activity participation. These factors encompass socio-demographic elements such as age, gender, education level, partnership status, unemployment duration, and health status, as well as psychological, physical, informational, and discrimination-related aspects (Benevenuto & Caulfield, 2019; Casas & Delmelle, 2014; Church et al., 2000; Dieckhoff & Gash, 2015; Kamruzzaman et al., 2016; Kunze & Suppa, 2017; Lättman et al., 2016; Pohlan, 2019; Yigitcanlar et al., 2019).

Economic insights into TRSE from a global perspective reveal distinct challenges between the global North and South, shaped by differing socio-economic and infrastructural contexts. While affordability and accessibility issues for citizens without car access predominate in the global North, the global South contends with a broader spectrum of obstacles, ranging from walking reliance in sub-Saharan Africa to urban planning and infrastructure quality in south and east Asia and South America (Lucas, 2011; Ureta, 2008; Wang et al., 2020).

This review also identifies a significant gap in the literature. Despite strong evidence of a vicious cycle between labor market marginality and poverty and social isolation (Gallie et al., 2003), and acknowledging transport's significant role in both social exclusion (Allen & Farber, 2020; Church et al., 2000; Currie et al., 2010; Lucas, 2012; Luz & Portugal, 2022; Yigitcanlar et al., 2019) and labor market outcomes (Bastiaanssen, 2012, 2020; Korsu & Wenglenski, 2010), research has yet to address how employment status combined with transport disadvantage affects participation in a wide range of activities beyond the labor market. This gap highlights the potential of transport and land use policies not only in addressing this complex interplay but also in potentially limiting or breaking the cycle of social and economic marginalization.

Three studies most aligned with this oversight are Luz et al. (2022) in Sao Paulo, Brazil, Cheng et al. (2019) in Nanjing, China, and Cordera et al. (2017) in Santander, Spain. These studies collectively contribute to our understanding of transport disadvantage among economically disadvantaged groups and its impact on diverse activity participation. Luz et al. (2022) highlight how limited accessibility, particularly through public transport, restricts low-income individuals' engagement in various activities, particularly discretionary ones, thereby increasing their risk of TRSE.

Similarly, Cheng et al. (2019) reveal the distinct travel patterns of low-income commuters, including longer durations in subsistence activities and reliance on alternative transport modes due to lower car ownership. Cordera et al. (2017) show that increased accessibility reduces private vehicle use for work but boosts the use of other modes for non-mandatory purposes, with household income not being a significant factor in trip production. However, it's noteworthy that while these studies shed light on the relationship between transport disadvantage and activity participation among low-income groups, they do not specifically focus on the unemployed, revealing a gap in the literature that warrants further investigation.

The insights from Luz et al. (2022), Cheng et al. (2019), and Cordera et al. (2017) underscore how economic disadvantages shape activity participation patterns through restricted or facilitated access to transport. These studies, along with additional research, are summarized in Table 3.1, which details evidence on the compensatory mechanisms in activity participation influenced by various forms of economic disadvantage and inducing factors.

Additionally, the studies by Buitelaar et al. (2021) and Kunze & Suppa (2017) are also included in Table 3.1 and reveal respectively that restricted out-of-home work and unemployment can lead to compensatory behavior in activity participation. For example, Buitelaar et al. (2021) observed that Dutch workers, when restricted from work-related activities during the COVID-19 lockdown, increased their participation in non-work-related activities. Similarly, Kunze & Suppa (2017) explore the relationship between unemployment and public activity participation. The study notes that while social stigma associated with unemployment often leads to reduced participation in public activities, it also prompts increased involvement in volunteering as an alternative to formal employment.

This thesis emphasizes the need to examine how transport accessibility and car availability significantly influence these compensatory behaviors in out-of-home activity participation, particularly under the constraints of unemployment, highlighting the critical role of transportation in enabling or restricting social inclusion.

In summary, the reviewed literature offers a comprehensive analysis of how transport disadvantage, economic disadvantage, and social exclusion are interconnected across different geographic contexts. It highlights the pivotal role of car access in the global North and details the unique challenges in the global South, such as reliance on walking and the impact of urban planning. Despite these insights, the literature also reveals significant research gaps, particularly in understanding the full spectrum of activity participation among the unemployed. Furthermore, this review introduces the concept of compensatory behavior in activity participation, noting how unemployment can lead individuals to engage more in volunteering and other non-work-related activities as alternatives to formal employment. However, it also underscores that limited car availability and poor transport accessibility can significantly restrict the realization of this compensatory behavior.

Table 3.1: Overview of studies on compensatory mechanisms in activity participation.

Study	**Location**	**Economic Disadvantage**	**Decrease**	**Increase**	**Inducing Factor**
Luz et al. (2022)	Sao Paulo, Brazil	Low-income	All, particularly discretionary activities	None specified	Lower transport accessibility
Cheng et al. (2019)	Nanjing, China	Low-income	None specified	Duration in subsistence activities	Lower car ownership
Cordera et al. (2017)	Santander, Spain	None specified	Work (private vehicle use)	Non-mandatory activities (other modes)	Increased accessibility
Buitelaar et al. (2021)	Netherlands	None specified	Work-related activities	Non-work-related activities	Work-from-home restrictions
Kunze & Suppa (2017)	Germany	Unemployment	Public activities	Volunteering	Social norms and stigma

4 Data

The Data chapter plays a crucial role in delineating the empirical foundation upon which this thesis is built. It specifically addresses the use of two pivotal datasets: the 'Onderweg in Nederland (ODiN)' surveys from 2018 and 2019, which provide extensive socio-demographic and travel behavior data, and an accessibility dataset that enumerates accessible jobs by car, public transport, and bicycle based on a log-logistic travel time decay function. These datasets are combined to explore how transport disadvantage, and its socio-demographic determinants, influence travel behavior and out-of-home activity participation among the unemployed. The process employed to integrate and prepare these datasets for the application of the methodology will also be outlined, providing a comprehensive view of the analytical processes used in the thesis. The chapter further delves into the definition and measurement of the key variables: transport accessibility, car availability, socio-demographic determinants, residential location, activity participation, and travel behavior outcomes.

The utilized data was provided by the Netherlands Environmental Assessment Agency (PBL). This data comprises two key elements: firstly, the ODiN survey from 2018 and 2019, rich in detail on socio-demographic characteristics, travel behavior, and car availability; secondly, a dataset from Bastiaanssen (2020) incorporating accessibility information, indicating the number of jobs reachable by car, public transport, and bicycle, formulated through a log-logistic travel time decay function. The integrated dataset obtained from enriching the ODiN data with the accessibility data is instrumental for illuminating the patterns of transport accessibility and car availability among unemployed individuals in the Netherlands and their participation in out-of-home activities.

The analytical work was primarily conducted within the secure digital ecosystem of the PBL. For the execution of the LCCA, data pertaining exclusively to unemployed individuals—encompassing variables on accessibility, car availability, and socio-demographic information—were carefully transferred to the TU Delft virtual Weblogin environment. Afterward, the LCCA results were moved to the PBL digital environment for the final analysis steps. This data transfer protocol was deliberately designed to minimize the amount of information transferred and restrict its storage to highly secure digital environments. The digital environments of PBL and TU Delft, characterized by their robust security features, are ensured against access by third parties, thus adhering to the existing data confidentiality and security obligations.

4.1. ODiN 2018 and 2019 dataset

The 'Onderweg in Nederland (ODiN)' 2018 and 2019 studies are comprehensive research projects aimed at shedding light on the daily mobility patterns of the Dutch population, thereby supporting the Ministry of Infrastructure and Water Management along with other policy and research institutions in their efforts to shape and assess transportation policies (CBS, 2018b). The ambition behind ODiN is not just to capture the everyday travel behaviors of individuals but to create a dataset that informs the development of transportation initiatives and strategies across the Netherlands.

The choice of the most recent pre-COVID-19 years for data collection acknowledges that out-of-home activity participation during the pandemic was severely limited by governmental restrictions, rendering this dataset slightly outdated yet the best available reflection of normal conditions. This temporal context is crucial for interpreting the data's applicability to current and future urban and transportation planning.

The core of ODiN consists of a baseline survey conducted on a national level, augmented by potential additional studies to ensure a thorough analysis of the mobility trends within the country. This baseline survey delves into the travel behavior of individuals, asking participants to detail their travel activities for a specific day, including destinations, purposes, transportation modes, and journey durations. Additionally, the survey collects information on (electric) bicycle ownership, average use of different transport means, and demographic details like education and social standing, aiming to encompass all daily movements on national territory, also during holiday periods, by Dutch residents aged 6 and above.

The methodology of the ODiN study is meticulously structured into three main phases: sample selection, fieldwork, and data processing. The process begins with selecting a representative sample of the population, where individuals are chosen and assigned a specific weekday to report their travel activities. The fieldwork phase then involves the dissemination of survey materials and the accumulation of responses, which are encoded into a database for subsequent analysis. A critical step in the data processing phase is the application of personal-level weights to the data to ensure its representativeness of the entire Dutch population, accounting for sample time, sample location, corrections for late responses, and demographic and socio-economic factors.

While you may argue against using these weights due to differences in certain characteristics such as age, income, and vehicle ownership between the general population and the unemployed, the benefits of employing this weighted approach outweigh the concerns. Elements such as sample time, sample location, and corrections for late responses are highly impactful in representing the entire unemployed population based on the sample, as they form a large part of the weighing elements (CBS, 2018b). These weights, designed to mirror the entire population, thus provide a valuable framework for extrapolating individual responses to all unemployed residing in the Netherlands.

4.2. Accessibility dataset

In this study, the dataset for accessibility is proxied by local-area job accessibility measures for each four-digit postcode area in the Netherlands, which approximates around 4080 areas with about 1000 households each. This dataset was developed in Bastiaanssen (2020), which utilizes the gravity model originally proposed by Hansen (1959). This model is employed to account for the diminishing appeal of destinations that are farther away, recognizing that attractiveness decreases with distance.

Job accessibility may be used well to (roughly) express relative differences in general accessibility, as jobs are typically distributed throughout urban areas, where other kinds of activities such as health care, shopping, leisure, and social activities also typically exist, and thus access to jobs can be a reasonable indicator of overall accessibility (Martens & Bastiaanssen, 2019). Considering car, public transport, and bike accessibility, this metric gives a rounded view of differential abilities to access essential services. While job accessibility is used as a proxy of overall accessibility, the methodology allows for this to be replaced with other forms of accessibility, allowing for more nuanced accessibility measurement.

The equation representing the accessibility measure is as follows:

$$A_{im} = \sum_{j} E_j f\left(T_{ij}\right), \tag{4.1}$$

where A_{im} indicates the accessibility to employment opportunities by transport mode m in the postcode area i, E_j denotes the number of jobs available in the destination area j, and $f(T_{ij})$ is a decay function based on travel times between areas i and j.

For this assessment, public transport travel times were gauged using a General Transit Feed Specification (GTFS) dataset, which provided a snapshot of timetable-based journey times during morning peak hours in 2016. This was complemented by a transport network from OpenStreetMap. The calculated travel times encompass various components including the time taken to access and wait at a public transport stop, the in-vehicle travel time, any transfer time, and the egress time to the employment locations.

Travel times by car and bicycle were estimated using OpenStreetMap data in conjunction with TomTom SpeedProfiles© to take congestion into account. The employment data used to calculate the accessibility measures originated from the National Employment Database of 2017 (Landelijk Informatiesysteem Arbeidsplaatsen - LISA), which is a comprehensive census of all registered businesses in the Netherlands, including the number of jobs per business sorted by postcode area.

Finally, the job accessibility measures—as proxies for overall accessibility—were computed based on a gravity model that discounts jobs through a travel-time-based impedance function, for which a (best fit) log-logistic function on observed trip travel times of commuters was used from the Dutch National Travel Survey (OViN 2017). OViN 2017 is the direct predecessor of ODiN 2018 (CBS, 2017).

4.3. Data preparation and cleaning

The first step in the data preparation and cleaning process involved filtering the ODiN dataset to focus on individuals based on their employment status. This included both unemployed individuals and those employed, whether on a part-time or full-time basis. This selection was fundamental to my research, as it allowed for a comparative analysis of out-of-home activity participation across different employment groups.

Following the selection based on employment status, I further refined the dataset by choosing variables critical to my analysis. These variables encompassed car availability, socio-demographic information, and travel behavior details regarding each trip made by the respondents. This step was crucial in streamlining the dataset, ensuring that only relevant data were carried forward for analysis.

Subsequently, I cleaned and transformed the data to address any inconsistencies or missing values, a step essential for maintaining the quality of the dataset. For example, I standardized the formats of the four-digit-level postal codes to ensure consistency across datasets, which was particularly important for accurately merging the travel diary data with the accessibility indices.

The merging process involved combining the ODiN dataset with the accessibility dataset based on four-digit-level postal codes, enriching the travel data with information on accessibility by car, public transport, and bicycle. This integration was vital for analyzing the impact of transport accessibility on the out-of-home activity participation of unemployed individuals.

4.4. Variable definitions and measurements

The selection and operationalization of variables in this study are meticulously crafted to encapsulate the complexities of transport accessibility and car availability as they relate to unemployed individuals in terms of their socio-demographic characteristics, residential locations, and patterns of out-of-home activity participation. The methodical approach to defining these variables takes into account highly relevant socio-demographic determinants of transport disadvantage and desired out-of-home activity participation, the urbanization level of residential locations, and patterns of out-of-home activity participation. This comprehensive framework aims to identify the critical indicators that can reveal the nuanced transport disadvantages that may hinder the unemployed from being socially included.

4.4.1. Car availability and accessibility group indicators

Car availability is a multifaceted concept that cannot be encapsulated by a singular indicator due to its inherent complexity. This complexity stems from the reality that car availability goes beyond mere possession of a personal vehicle or holding a driver's license. For example, individuals lacking personal vehicles or licenses may still have substantial access to a car as passengers, particularly when other members within their household own vehicles and have driving privileges. Additionally, holding a driver's license can enhance an individual's car availability in ways that are both dependent and independent of owning a car, through options such as car rentals or borrowing from within one's social network. Ownership of a car itself is a significant contributor to car availability, offering a higher degree of personal mobility.

Given the diverse nature of car availability that arises from the interplay of car ownership, driver's license possession, and the number of cars within a household, it is imperative to consider these dimensions collectively. In this study, variables have been defined and modified to reflect the comprehensive nature of transport disadvantage through transport accessibility and car availability, informed by insights from the literature. As highlighted by Bantis & Haworth (2020), Bastiaanssen & Breedijk (2022), and Martens & Bastiaanssen (2019), the spatial accessibility to amenities and opportunities is paramount to understanding social inclusion and mobility. Recognizing that spatial factors significantly influence accessibility, I have included spatial accessibility measures for car, public transport, and the bike.

To align with the literature's focus on the importance of car availability as a primary determinant of transport disadvantage (Gao et al., 2022; Lucas, 2012; Martens et al., 2019; Mattioli, 2021), car ownership was categorized into '0' for individuals without a car and '1 or more' for those with at least one car. This dichotomization addresses the reality that particularly in less urbanized areas, car access significantly limits transport disadvantage.

The binarization of car ownership was informed by the observation that only a negligible number of individuals, 63 to be precise, reported owning two or more cars. Moreover, the distinction between having one car versus having multiple cars was deemed inconsequential for this analysis, as the car availability difference between owning one and owning more than one was presumed negligible.

Similarly, the variable measuring cars in the household was categorized into three groups: households without a car ('0'), with one car ('1'), and with two or more cars ('2 or more'). This classification was guided by the fact that only a marginal number of households, 79 in total, reported having three or more cars. Here similarly, it was assumed that the difference in car availability between households with two cars and those with more than two was negligible for the analysis. For the three respondents whose number of cars in the household was unknown, this was imputed as one, which is the mode of the distribution and therefore the most likely value. This imputation also ensures the smallest share-weighted deviation from the other two categories.

The summarization of these indicators, as well as the distributions of transport accessibility and car ownership measures, is encapsulated in Table 4.1. The table shows several distributional statistics for the car, public transport, and bicycle accessibility indicators. These indicators display the number of jobs within reach based on a log-logistic travel time decay function. Furthermore, it provides a breakdown of car ownership, driver's license possession, and cars within a household, offering a quantitative picture of the car-availability-related attributes of the unemployed.

Table 4.1: Descriptive statistics of the LCCA transport disadvantage indicators.

		Mean	SD	Median	Min	Max
Accessibility (thousands of jobs based on log-logistic travel time decay function)	Car	1280	555	1400	0	2200
	Public transport	154	144	103	0	665
	Bike	50.2	43.7	35.8	0	218
		Count	**Share**			
Car availability	*Car ownership*					
	0	1110	60.3%			
	1 or more	730	39.7%			
	Driver's license possession					
	Yes	1323	71.9%			
	No	517	28.1%			
	Cars in household					
	0	582	31.6%			
	1	827	45.0%			
	2 or more	431	23.4%			

n = 1840 unemployed individuals, one day of travel diary data per individual. Car availability data originates from the ODiN travel diary dataset for the years 2018 and 2019, accessibility dataset from Bastiaanssen (2020).

4.4.2. Socio-demographic determinants

This subsection meticulously details the selection and operationalization of key socio-demographic variables: gender, age, household type and individual position, education level, standardized disposable household income (adjusted for a one-person household), and (parental) birthplace. Drawing on the framework established by Kamruzzaman et al. (2016) and studies outside the transport domain (Dieckhoff & Gash, 2015; Pohlan, 2019), these factors are recognized for their critical role in understanding social exclusion. The socio-demographic characteristics provide the foundation for a nuanced understanding of their influence on individual transport needs and how they contribute to transport disadvantage, thereby affecting participation in out-of-home activities. The distributions of these socio-demographic factors are detailed in Table 4.2.

Gender is a critical determinant due to its interrelation with not just economic disadvantage but also with discrimination-based TRSE. Additionally, there is the gender-influenced psychological dimension of TRSE, including issues of safety and security during travel. Further, gender differences impact transportation needs and, consequently, out-of-home activity participation. For instance, across cities as varied as Auckland, Dublin, Hanoi, Helsinki, Jakarta, Kuala Lumpur, Lisbon, and Manila, a consistent trend is observed among women: they tend to travel shorter distances and have a higher preference for public

Table 4.2: Descriptive statistics of the LCCA socio-demographic active covariates.

	Count	Share
Gender		
Male	913	49.6%
Female	927	50.4%
Age		
15-34	455	24.7%
35-54	704	38.3%
55^{+}	681	37.0%
Household type and individual position		
Single person	521	28.3%
Single person with children	118	6.41%
Partner with children	462	25.1%
Partner without children	517	28.1%
Child	178	9.67%
Other	44	2.39%
Education level		
None	74	4.02%
Low	437	23.8%
Intermediate	638	34.7%
High	634	34.5%
Other	57	3.10%
Standardized disposable household income group		
First quintile (lowest)	669	36.4%
Second quintile	300	16.3%
Third quintile	247	13.4%
Fourth quintile	236	12.8%
Fifth quintile (highest)	293	15.9%
Unknown	95	5.16%
*(Parental) birthplace**		
The Netherlands	1104	60.0%
Outside the Netherlands	736	40.0%

n = 1840 unemployed individuals. Data originates from the ODiN travel diary dataset for the years 2018 and 2019.
*Classified as the Netherlands in case the individual and both of their parents were born in the Netherlands. Any other combination of birthplace and parent's birthplace is classified as outside the Netherlands.

transport over cars compared to men (Ng & Acker, 2018). Conversely, Pohlan (2019) demonstrates that unemployed men are particularly vulnerable to social exclusion.

Age is another determinant, factored into the analysis for its influence on the desired out-of-home activity participation. It is also relevant to the physical dimension of TRSE, such as disabilities, and to informational exclusion, which encompasses ICT abilities. Age has been categorized into three groups: 15-34, 35-54, and 55+, to reflect varying transportation needs and accessibility challenges across the lifespan. This categorization draws from findings in Germany, where the likelihood of households owning more cars grows with the age of the household head, reaching a peak in the 35-44 age bracket, and then declines sharply for those over 55 years old (Prillwitz et al., 2006).

Household type and individual position also significantly influence out-of-home activity participation and are thus included in the analysis. Household size has been shown to positively influence car ownership. In fact, in the Netherlands in 2014, household size accounted for 35% of the total effect on car ownership when considering economic, socio-demographic, and spatial factors (Maltha et al., 2017). Furthermore, Pohlan (2019) shows that those without a supportive partnership are at a higher risk of social exclusion.

The inclusion of education level as a socio-demographic determinant is motivated by its interplay with economic and transport disadvantage. Education not only influences employment opportunities and income levels, thereby affecting economic status, but also shapes individuals' mobility patterns (Molin et al., 2016), access to information, and their capacity to navigate transport systems. Outside the transport domain, it is often mentioned that those with lower education levels are at a higher risk of social exclusion (Dieckhoff & Gash, 2015; Pohlan, 2019). Education level is classified according to a modification of the Dutch education system classification, as performed by Statistics Netherlands, utilizing the UNESCO International Standard Classification of Education, Fields of Education and Training (ISCED-F 2013) framework (CBS, 2022b).

This adaptation results in a hierarchical structure of three main educational levels: low, intermediate, and high. Additionally, two distinct categories are identified to accommodate cases that do not conform to this classification: 'no education' and 'other'. This categorization reflects a comprehensive approach to capturing the range of educational achievements within the dataset, aligning with international standards to ensure consistency and comparability in the analysis.

Disposable household income refers to the amount of income available to a household after deducting various expenses from the gross income. These expenses include payments for income transfers such as alimony to a former spouse, premiums for income insurance (which cover social insurances, national insurances, and private insurances related to unemployment, disability, old age, and death), health insurance premiums, and taxes on income and wealth (CBS, 2018a).

The concept of standardized disposable income adjusts this disposable income to account for differences in household size and composition. This adjustment is made using equivalence factors, which lower income levels with increasing numbers of adults and children within a household but also reflect scale benefits achieved by maintaining a common household (CBS, 2022a). Essentially, these factors adjust incomes to the level of a single-person household, allowing for a fair comparison across different households. Through this standardized measure, the disposable income of households of various sizes and compositions can be uniformly compared as if they were all single-person households.

Standardized disposable household income is an indispensable socio-demographic variable, as it is closely linked to car ownership in the Netherlands (Bastiaanssen & Breedijk, 2022). Income levels often delineate the balance between spatial accessibility and car ownership, with lower-income groups typically facing greater constraints in this regard (Mattioli, 2017). Canadian studies reveal that low-income households endure longer commute times more frequently than the population average, suggesting similar trends may be present elsewhere (Allen et al., 2022). Income not only affects the ability to own and maintain a vehicle but also dictates which out-of-home activities individuals can participate in, considering affordability. Income is thus highly influential regarding an individual's overall transport disadvantage and out-of-home activity participation.

In analyzing the complex interplay between unemployment and transport disadvantage on out-of-home activity participation, this study incorporates (parental) birthplace as a proxy for discrimination-based exclusion, recognizing its role among various interacting social disadvantage factors. This dummy variable, defined by having at least one parent or being born oneself outside the Netherlands (CBS, 2024a), aims to capture the effects of discrimination on TRSE. However, it's acknowledged as a very noisy measure due to the heterogeneity within both groups categorized by (parental) birthplace.

The (parental) birthplace classification may align with broader patterns of discrimination, suggesting that individuals with a (parental) birthplace outside the Netherlands typically face more discrimination. However, this system can misclassify many cases that exist in the Netherlands, leading to discrepancies in the presumed experience of discrimination. For example, the (parental) birthplace of individuals with one parent from a neighboring country is classified as outside the Netherlands and they might be presumed to face discrimination, despite potentially experiencing little to none.

Conversely, those with a (parental) birthplace classified as Netherlands and having foreign ancestry, could face discrimination, contradicting the general assumptions of their classification. This highlights the measure's limitations in accurately representing the nuanced experiences of discrimination among different individuals. Despite its limitations, including (parental) birthplace is considered useful for a holistic understanding of how social disadvantages intersect with transport and economic factors, as outlined in the literature review Section 3.3 - Interacting social disadvantage factors.

4.4.3. Activity participation and other travel behavior outcomes

Activity types were categorized into ten distinct categories to capture the type and frequency of engagement, which are critical dimensions for a comprehensive measure of activity participation (Kamruzzaman et al., 2016). The categorization of activities even includes both work and business-related activities. This inclusivity is motivated by the definition of unemployment not precluding unpaid or informal work, alongside active job search; unemployment is characterized by the absence of paid employment while actively looking and available for work (CBS, 2024b).

The transformation from individual trips to activity participation drew upon the methodology proposed by Allen & Farber (2020). As illustrated in Figure 4.1, this conversion entails mapping each trip to its associated activity. For instance, a single round trip from home to work is considered two trips contributing to one activity. Similarly, a multi-stop journey involving stops at a shop, café, and returning home constitutes three trips that facilitate two separate activities: shopping and visiting a café. A more complex journey that includes trips to work, a café, and other leisure destinations before returning home would count as five trips but three distinct activities. Descriptive statistics of the activity participation and other travel behavior outcomes may be viewed in Table 4.3.

The travel behavior outcomes of the time of travel (travel period), the mode of transport used (mode usage), total travel distance, and time spent traveling were incorporated into the study. These aspects provide essential insights into the 'when', 'how', the spatial extent, and the time burden of travel behaviors, which are critical for formulating targeted transport and urban planning policies. Such policies can be directed to improve out-of-home activity participation among various transport disadvantaged groups, ensuring that interventions are precisely attuned to the identified needs and barriers within the unemployed population.

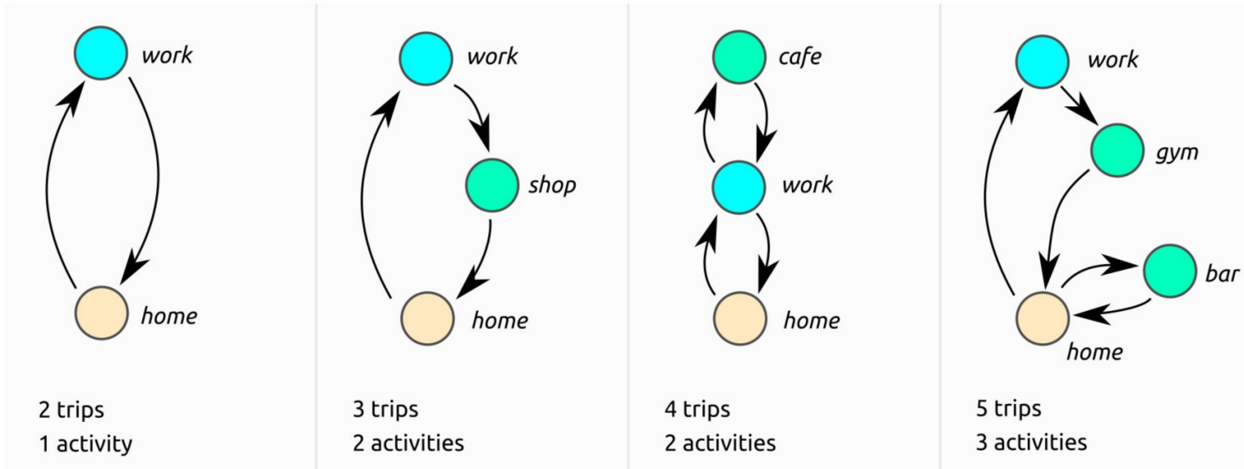


Figure 4.1: Trips to activities examples.
From Allen & Farber (2020).

In detailing the travel period data, de Haas (2020) display the distribution of car travelers throughout an average working day in quarter-hour intervals, utilizing the ODiN 2018 dataset. This study displays each quarter-hour of the day as a measurement point, capturing trips that span multiple quarter-hour blocks. From this analysis, morning peak hours are identified between 6:30 to 9:00, and evening peak hours from 16:00 to 18:30, coinciding with the peak commuting times recognized by Dutch Railways (NS, 2024), the largest public transportation provider in the Netherlands. I consider peak periods for cars and public transport since cycling and walking are notably less affected by peak traffic times. To classify trips within specific periods based on departure and arrival times found in the data, the midpoint between these times is logically taken as the most representative moment of the trip.

4.4.4. Residential location

The study's incorporation of urbanization levels serves to contextualize the residential environments of unemployed individuals in relation to their transport accessibility and car availability. Five urbanization levels have been delineated: highly urbanized, strongly urbanized, moderately urbanized, slightly urbanized, and non-urbanized areas. This categorization provides a framework within which to examine the car availability and accessibility data, offering a perspective on how these variables interact with the degree of urbanization and the socio-demographic covariates.

This urbanization-level approach to understanding residential location serves as a key variable for analyzing spatial inequalities in transport accessibility and car availability. It provides insights into the geographic distribution of transport disadvantage and informs tar-

Table 4.3: Descriptive statistics of the LCCA travel behavior distal outcomes and residential location inactive covariates.

		Mean	SD	Median	Min	Max
Activity participation (number of out-of-home activities across all individuals)	Total	1.45	1.51	1	0	9
	Work	0.0967	0.378	0	0	5
	Business or occupational	0.00543	0.0806	0	0	2
	Groceries or shopping	0.476	0.720	0	0	6
	Transporting people or goods	0.234	0.698	0	0	6
	Education	0.0261	0.173	0	0	2
	Social visit	0.164	0.433	0	0	3
	Social and recreational other	0.240	0.553	0	0	6
	Touring or hiking	0.118	0.404	0	0	4
	Services or personal care	0.0745	0.294	0	0	2
	Other	0.0201	0.152	0	0	2
	Travel distance (in km)	24.8	44.8	8.0	0	408
	Travel time (in minutes)	70	80	48	0	600
Travel period (number of trips across all individuals)	*Weekday*					
	Night (0:00-6:30)	0.00761	0.0930	0	0	2
	Morning peak (6:30-9:00)	0.187	0.525	0	0	4
	Between peaks (9:00-16:00)	1.20	1.58	0	0	9
	Afternoon peak (16:00-18:30)	0.304	0.676	0	0	5
	Evening (18:30-23:59)	0.241	0.617	0	0	5
	Weekend or national holiday					
	Night (0:00-6:30)	0.0114	0.111	0	0	2
	Day (6:30-18:30)	0.501	1.16	0	0	10
	Evening (18:30-23:59)	0.100	0.395	0	0	4
Mode usage (number of trips across all individuals)	Public transport	0.123	0.487	0	0	4
	Car (driver)	0.842	1.62	0	0	14
	Car (passenger)	0.231	0.739	0	0	6
	Bike	0.695	1.38	0	0	9
	Walk	0.598	1.14	0	0	10
	Other	0.0620	0.454	0	0	7
		Count	**Share**			
Residential location	*Urbanization level*					
	Highly urbanized	604	32.8%			
	Strongly urbanized	597	32.4%			
	Moderately urbanized	244	13.3%			
	Slightly urbanized	281	15.3%			
	Non-urbanized	114	6.2%			

n = 1840 unemployed individuals, one day of travel diary data per individual. Data originates from the ODiN travel diary dataset for the years 2018 and 2019.

geted policy interventions that can enhance mobility and access for unemployed individuals across various urbanization contexts.

5
Transport accessibility and car availability groups

This chapter explores the intersection of transport accessibility, car availability, and the socio-demographic and urbanization profiles of unemployed individuals in the Netherlands. Utilizing LCCA, I discern eight distinctive groups characterized by their unique transport disadvantage patterns. These classifications serve as a lens through which the varied experiences of out-of-home activity participation are examined in subsequent analyses, emphasizing how socio-demographic determinants shape accessibility, car availability, and out-of-home activity participation.

5.1. Model estimation

In selecting the optimal number of latent classes for the LCCA model, I sought a configuration that would most effectively elucidate the research questions. Conventional model fit statistics are not decisive in isolation; however, when considering the variation in transport accessibility and car availability across clusters, the resultant eight-class model distinguishes itself. It unveils a broad spectrum of patterns of accessibility and car availability that are vital for a nuanced examination of the research questions, which pivot on transport-related limitations and their implications for activity participation.

The visual mapping of the clusters, as illustrated in Figure 5.1, offers a compelling depiction of the inter-cluster differences in transport accessibility and car availability. The clusters are arrayed against the backdrop of the hypothesized TRSE-risk, grounded in the premise that transport limitations can hinder participation in out-of-home activities. Figure 5.1, capturing the essence of the eight-cluster analysis, clearly exhibits the hypothesized relationships.

The mapping onto the accessibility and car availability plane was manually executed, considering the within-cluster accessibility and car availability distributions relative to the sample's total distribution, as detailed in Table 5.4.

The mapping and naming convention for the clusters adheres to the format of 'relative level of accessibility'-'relative level of car availability', reflecting a coherent synthesis of the multifaceted indicators. Despite the existence of three indicators for both transport accessibility and car availability to comprehensively represent these dimensions, the indicators within each cluster tend to align in the same direction and, almost exclusively, with a similar magnitude. This congruence allows for the clusters to be succinctly described by the aforementioned format, offering a clear and direct characterization of each cluster's distinct combination of accessibility and car availability attributes.

By examining clusters that represent almost the entire spectrum of accessibility and car availability—from very low to very high—I can assess the potential transport limitations in out-of-home activity participation. This approach allows for a comparison across the clusters, facilitating a deeper understanding of how unemployment, coupled with transport accessibility and car availability, influences out-of-home activity participation.

In summary, the eight-class configuration enriches our comprehension of the underlying patterns within the data, aligning closely with the research objectives. It enables a robust analysis that provides a foundational base for the development of informed transport and land use policies aimed at enhancing the social inclusion of the unemployed.

5.1.1. Model fit statistics and architecture

In selecting the optimal number of latent classes for the LCCA model within my study, conventional model fit statistics present significant challenges. The model fit statistics in Table 5.1 represent consecutive model estimations starting with a model with one class, up to and including a model with ten classes. Model estimation resulted from estimating solely the measurement model part of the LCCA, thus excluding covariates, and was performed in the Latent Gold 6.0 software package (Vermunt & Magidson, 2005a). The Vuong-Lo-Mendell-Rubin (VLMR) likelihood ratio chi-squared statistic (Lo et al., 2001; Vuong, 1989), as indicated in Table 5.1, is not a suitable motivator for the number of latent classes due to the rejection of all models from 1 to 10 clusters.

Moreover, minimizing the Bayesian Information Criterion (BIC), which provides a way to account for both model parsimony and model fit, continually decreases as the number of

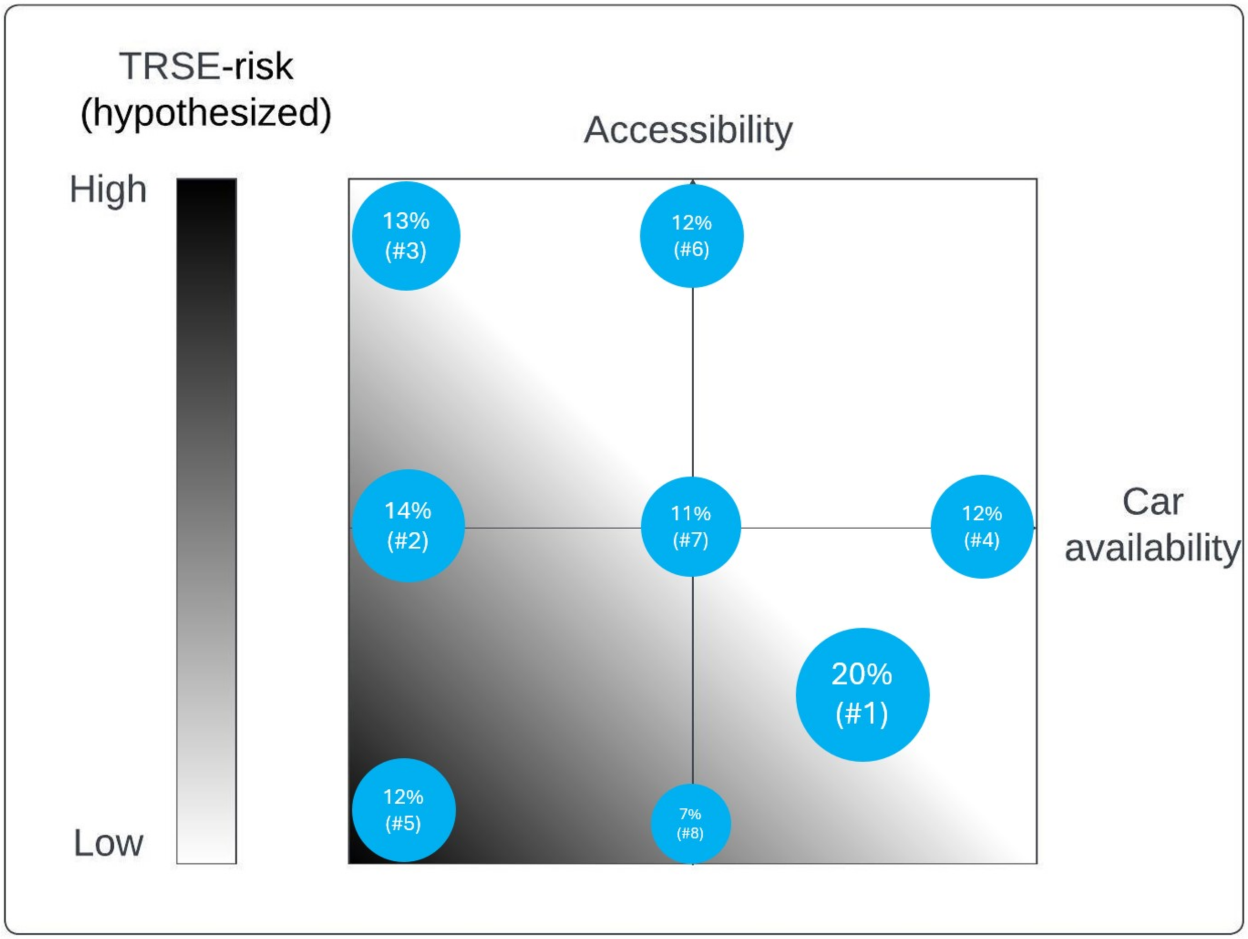


Figure 5.1: Mapping of each cluster onto the indicator-profiles-derived accessibility and car availability plane, on the backdrop of the hypothesized TRSE-risk due to transportation-limited out-of-home activity participation.
Note: Clusters are visualized as circles sized proportionally to their sample size percentages, with numbers indicating their size ranking from largest (#1) to smallest (#8).

clusters increases. However, adopting a model with 10 or more clusters poses significant interpretative challenges and would be overly complex for communication purposes. Additionally, the maximum bivariate residual statistic, substantially exceeding the 3.84 threshold (indicative of a 5% significance level to reject local dependence) for all models, does not offer clear-cut guidance for selecting a particular number of latent classes.

Table 5.1: Model fit statistics LCCA measurement models (without covariates).

Number of classes	Number of parameters	LL	VLMR	p-value	BIC(LL)	Max BVR	Classification error	Entropy R^2
1	11	-13236945			26474037	477634	0.0000	1.0000
2	21	-12385559	1696773	0.000	24777398	225004	0.0277	0.9001
3	31	-12086067	605061	0.000	24172466	133262	0.0422	0.8922
4	41	-11962067	247920	0.000	23924680	133243	0.0480	0.8849
5	51	-11883558	157507	0.000	23767756	58044	0.0698	0.8849
6	61	-11815842	135394	0.000	23632496	42522	0.0774	0.8774
7	71	-11752879	115124	0.000	23515705	44293	0.0943	0.8743
8	81	-11723688	69183	0.000	23448545	26000	0.1094	0.8675
9	91	-11676628	94120	0.000	23354468	17151	0.1010	0.8757
10	101	-11652873	47511	0.000	23307090	11604	0.1142	0.8670

LL: Final log-likelihood of the model. VLMR: Vuong-lo-mendell-rubin likelihood ratio chi-squared statistic (Lo et al., 2001; Vuong, 1989). BIC(LL): Bayesian information criterion (based on log-likelihood). Max BVR: Maximum bivariate residual.

Given these statistical constraints, the justification for selecting eight latent classes is rooted in the capacity of this model to address the research questions effectively. After including the socio-demographic active covariates in new model estimations ranging again from 1 class to 10 classes, the within-cluster distributions of indicators in the estimated 8-class model reveal distinct patterns of accessibility and car availability that enable a detailed answering of the research questions.

Latent Gold reveals insightful pseudo R-squared statistics for the 8-class model incorporating covariates, where the standard R-squared measure—a quantitative measure rooted in variance explanation (Vermunt & Magidson, 2005a)—achieves an impressive 0.89. This high value signifies that the model adeptly captures a vast majority of the variance in class membership attributable to the active covariates.

Accordingly, both the measurement and structural model's parameters all exhibit joint high significance for each included indicator and active covariate, as can be seen from the Wald tests and associated p-values in Table 5.2 and Table 5.3, respectively. The structural model parameter Table 5.3 naturally omits the inactive covariate of residential urbanization level as it does not have any related parameters. My analysis predominantly draws on the detailed within-cluster distributions of both indicators and covariates, meticulously laid out in Table 5.4.

Table 5.2: Measurement model parameters and their corresponding z-values of the estimated 8-class latent class cluster analysis model.

	Intercept	z-value	Wald	p-value	Cluster 1	z-value	Cluster 2	z-value	Cluster 3	z-value	Cluster 4	z-value
Accessibility*	α_j				ζ_{jk}							
Car	1238	2846	8097716	0.000	-322	-238	193	191	617	844	215	140
Public transport	151	1310	1717324	0.000	-115	-1012	-22.9	-93.5	234	703	-20.8	-68.4
Bike	49.4	1280	1637135	0.000	-30.3	-703	-8.11	-120	71.3	462	-8.55	-125
	γ_{jc}				δ_{jk}							
Car ownership												
0	1.43	3.05	9.28	0.002	-1.74	-3.72	5.77	2.78	5.71	2.75	-7.13	-4.43
1 or more	-1.43	-3.05			1.74	3.72	-5.77	-2.78	-5.71	-2.75	7.13	4.43
Driver's license possession												
Yes	0.57	140	19630	0.000	0.767	89	-0.739	-142	-0.92	-171	1.3	49.5
No	-0.57	-140			-0.767	-89	0.739	142	0.92	171	-1.3	-49.5
	η_{jm}				τ_{jk}							
Cars in household (ordinal)					2.56	148	-4.62	-139	-4.29	-124	2.23	146
0	-0.106	-8.18	66212	0.000								
1	1.55	111										
2 or more	-1.44	-257										

	Cluster 5	z-value	Cluster 6	z-value	Cluster 7	z-value	Cluster 8	z-value	Wald	p-value	R^2
Accessibility*	ζ_{jk}										
Car	-743	-878	576	763	252	240	-788	-860	3005176	0.000	0.737
Public transport	-115	-821	191	514	-10.1	-35.7	-141	-1211	1920329	0.000	0.830
Bike	-27.7	-455	53.5	324	-6.41	-83.1	-43.8	-1079	1235988	0.000	0.730
	δ_{jk}										
Car ownership											
0	0.851	1.81	-1.53	-3.26	-0.227	-0.485	-1.7	-3.63	13475	0.000	0.574
1 or more	-0.851	-1.81	1.53	3.26	0.227	0.485	1.7	3.63			
Driver's license possession											
Yes	-0.757	-137	0.177	25.2	-0.517	-94.4	0.687	70.4	75105	0.000	0.299
No	0.757	137	-0.177	-25.2	0.517	94.4	-0.687	-70.4			
	τ_{jk}										
Cars in household (ordinal)	-3.08	-104	1.97	120	2.55	140	2.67	105	29447	0.000	0.668
0											
1											
2 or more											

* Defined by thousands of jobs based on log-logistic travel time decay function.

Table 5.3: Structural model parameters and their corresponding z-values of the estimated 8-class latent class cluster analysis model.

	Cluster 1	z-value	Cluster 2	z-value	Cluster 3	z-value	Cluster 4	z-value	Cluster 5	z-value	Cluster 6	z-value	Cluster 7	z-value	Cluster 8	z-value	Wald	p-value
Intercept (β_{0k})	0.745	2.60	0.092	0.320	0.655	2.29	0.109	0.378	0.374	1.31	0.362	1.26	0.161	0.563	-2.50	-1.25	2992	0.000
Covariate coefficients (β_k)																		
Gender																		
Male	0.214	58.7	-0.089	-21.8	-0.077	-18.0	0.354	83.3	0.054	12.6	0.062	14.5	-0.334	-62.2	-0.184	-34.6	13374	0.000
Female	-0.214	-58.7	0.089	21.8	0.077	18.0	-0.354	-83.3	-0.054	-12.6	-0.062	-14.5	0.334	62.2	0.184	34.6		
Age																		
15-34	-0.275	-40.5	0.38	58.3	0.268	39.9	-0.578	-55.4	0.422	62.4	-0.345	-41.9	0.100	11.8	0.028	3.00	18999	0.000
35-54	-0.007	-1.26	0.069	12.5	-0.006	-1.01	0.205	29.8	0.151	26.4	0.104	16.8	-0.267	-36.6	-0.249	-30.2		
55+	0.282	51.5	-0.45	-72.6	-0.262	-41.2	0.374	52.5	-0.573	-86.9	0.240	35.8	0.167	19.4	0.221	27.9		
Household type and individual position																		
Single person	-0.580	-54.4	0.945	93.6	0.869	89.3	0.663	22.2	0.634	67.5	-0.236	-21.8	-1.81	-68.0	-0.481	-37.2	70692	0.000
Single person with children	-0.129	-8.20	0.512	36.7	0.882	66.9	0.682	20.7	0.176	12.1	-0.647	-32.7	-1.21	-38.6	-0.271	-13.9		
Partner with children	0.487	55.5	-0.634	-54.1	-0.981	-84.9	0.704	27.1	-0.661	-58.9	0.146	15.2	0.887	73.4	0.052	4.22		
Partner without children	0.278	33.8	-0.064	-5.73	-0.337	-30.7	0.253	8.88	-0.425	-38.5	0.032	3.11	0.304	23.4	-0.041	-3.74		
Child	0.195	8.27	-0.420	-16.6	-0.464	-18.3	-2.13	-15.7	-0.376	-15.0	0.250	9.99	2.19	85.8	0.755	30.9		
Other	-0.250	-12.9	-0.339	-12.6	0.032	1.50	-0.171	-4.36	0.653	35.3	0.456	24.9	-0.366	-13.1	-0.014	-0.573		
Education level																		
None	1.27	1.11	1.40	1.22	0.933	0.815	1.34	1.17	1.85	1.61	1.23	1.07	0.346	0.302	-8.37	-1.04	23775	0.000
Low	-0.031	-0.109	-0.196	-0.684	-0.044	-0.155	-0.789	-2.76	-0.16	-0.558	-0.586	-2.04	-0.107	-0.374	1.91	0.955		
Intermediate	0.151	0.528	-0.317	-1.11	-0.969	-3.39	-0.228	-0.796	-0.322	-1.13	-0.172	-0.60	-0.234	-0.817	2.09	1.04		
High	-0.183	-0.638	-0.142	-0.494	-0.080	-0.281	-0.205	-0.717	-0.675	-2.36	0.012	0.041	-0.33	-1.15	1.60	0.801		
Other	-1.21	-4.22	-0.745	-2.60	0.161	0.562	-0.115	-0.401	-0.69	-2.41	-0.483	-1.68	0.326	1.14	2.76	1.38		
Standardized disposable household income group																		
First quintile (Lowest)	-0.465	-57.0	0.968	113	-0.002	-0.294	-0.564	-50.1	0.728	81.8	-0.243	-15.0	-0.625	-57.6	0.204	15.0	62542	0.000
Second quintile	-0.087	-9.78	-0.202	-16.8	-0.25	-23.9	0.084	7.31	0.093	8.25	0.229	13.6	-0.012	-1.15	0.145	9.80		
Third quintile	-0.035	-3.73	-0.76	-48.0	-0.529	-40.7	0.231	19.4	-0.001	-0.048	0.724	43.4	0.009	0.833	0.362	24.2		
Fourth quintile	0.418	41.6	-0.958	-45.0	-0.496	-28.9	0.994	76.2	-0.876	-41.7	0.551	29.0	0.093	7.62	0.274	17.1		
Fifth quintile (Highest)	0.545	57.1	-0.523	-28.1	0.025	1.86	0.402	31.4	-1.08	-49.1	0.787	44.8	0.243	21.1	-0.394	-20.8		
Income Unknown	-0.376	-14.7	1.48	80.4	1.25	70.2	-1.15	-29.4	1.14	56.6	-2.05	-28.0	0.292	12.4	-0.591	-11.2		
(Parental) birthplace																		
The Netherlands	0.357	81.0	-0.159	-37.5	-0.564	-122	0.106	22.0	0.191	41.7	-0.511	-112	-0.158	-30.7	0.738	103	47931	0.000
Outside the Netherlands	-0.357	-81.0	0.159	37.5	0.564	122	-0.106	-22.0	-0.191	-41.7	0.511	112	0.158	30.7	-0.738	-103		

5.2. Socio-demographic, residential urbanization, and transport disadvantage profiles

Figure 5.2 presents a visualization of clusters that align car availability and accessibility with socio-demographic and residential urbanization characteristics, set against the hypothesized gradient of TRSE-risk. The red clusters, constituting 61% of the unemployed sample, generally exhibit lower car availability and higher accessibility. This subset predominantly comprises younger individuals, those in single-person households, and members with lower household incomes. These individuals often have a non-native (parental) birthplace and are located in areas of high residential urbanization. The depiction underscores their potential reliance on public transportation or non-motorized travel modes, which is facilitated by their urban living context yet possibly constrained by socio-demographic factors.

In contrast, the green clusters in Figure 5.2 represent 39% of the sample and are associated with higher car availability and lower accessibility. These clusters are found in environments with lower residential urbanization, where accessibility to public transportation is very limited—suggesting that their car ownership is a critical component of their mobility. Members of these clusters are typically older and enjoy more favorable socio-demographic traits, such as higher household incomes, the support of multi-person households, and native (parental) birthplace.

Following this, the thesis provides a detailed exploration of each cluster or group, delving into the specificities of their car availability, accessibility, socio-demographic composition, and the degree of residential urbanization. Each group's mapping and naming convention follows the format of 'relative level of accessibility'-'relative level of car availability', as detailed in Section 5.1 - Model estimation.

For each cluster or group, the analysis begins with a delineation of its distinct pattern of accessibility and car availability indicators. This is succeeded by an examination of the socio-demographic active covariates that are instrumental in determining cluster membership, along with the inactive covariate of residential urbanization level. These steps are informed by the within-cluster distributions of the indicators and covariate variables, which are systematically presented in Table 5.4.

5.2.1. Group 1: low accessibility, high car availability (20%)

Comprising 19.8% of the sample, this group stands out for high car availability with the majority (65.4%) owning one or more vehicles. A significant share of members hold driver's

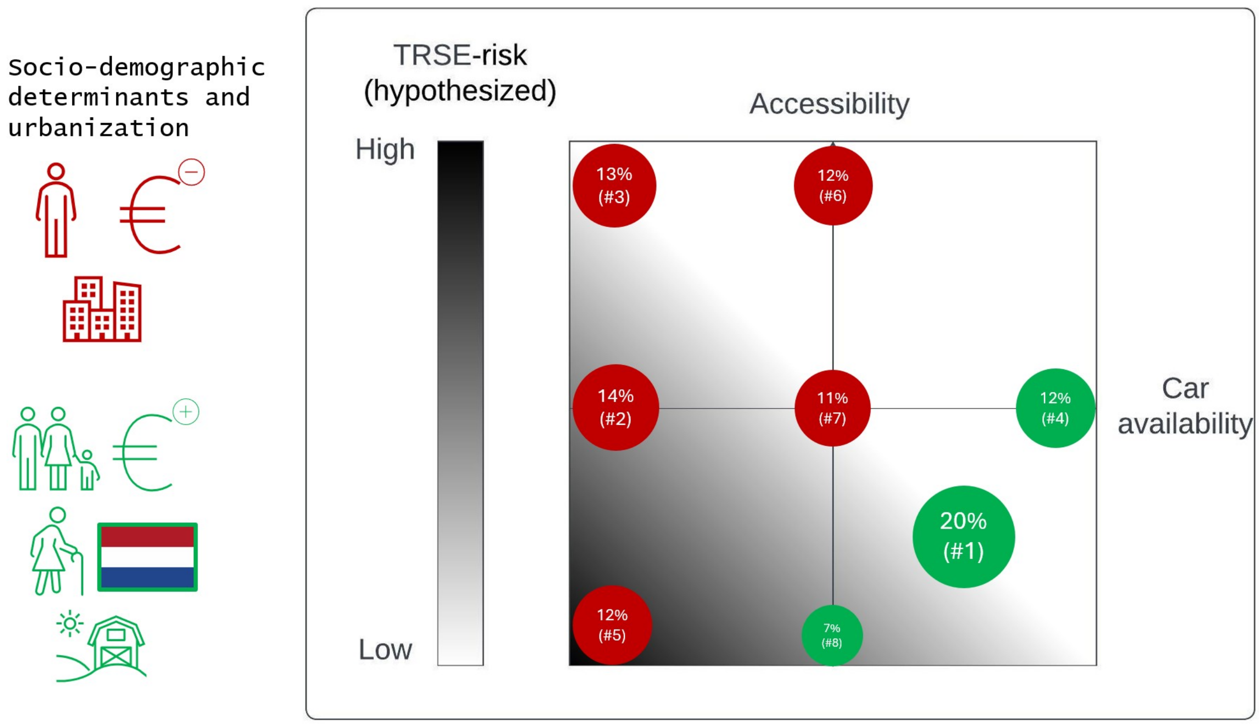


Figure 5.2: Mapping of each cluster onto the indicator-profiles-derived accessibility and car availability plane, with socio-demographic and residential urbanization level context. *Note: Clusters are visualized as circles sized proportionally to their sample size percentages, with numbers indicating their size ranking from largest (#1) to smallest (#8).*

Table 5.4: Within-cluster mean values and distributions of indicators and covariates.

	Clusters: accessibility-car availability								
	1: low-high	2: medium-very low	3: very high-very low	4: medium-very high	5: very low-very low	6: very high-medium	7: medium-medium	8: very low-medium	Sample total
Cluster size	20%	14%	13%	12%	12%	12%	11%	7%	
Indicators									
Accessibility*									
Car	917	1430	**1855**	1453	495	1814	1490	450	1259
Public transport	36.3	128	**385**	130	36.4	342	141	9.94	150
Bike	19.1	41.3	**121**	40.8	21.7	103	43.0	5.61	49.4
	%								
Car ownership									
0	34.6	**100**	**100**	0.00	**98.9**	45.0	**91.7**	36.7	**63.1**
1 or more	**65.4**	0.00	0.00	**100**	1.04	**54.9**	8.32	**63.3**	36.9
Driver's license possession									
Yes	**93.6**	41.6	33.2	**97.7**	40.8	**81.7**	**52.7**	**92.5**	**66.9**
No	6.44	**58.4**	**66.8**	2.31	**59.2**	18.3	47.3	7.48	33.1
Cars in household									
0	0.88	**95.1**	**93.3**	1.39	**80.6**	1.91	0.90	0.76	35.5
1	**59.9**	4.89	6.66	**67.1**	19.4	**71.9**	**60.2**	**57.4**	**42.7**
2 or more	39.3	0.00	0.00	31.5	0.05	26.2	39.0	41.9	21.8
	%								
Active covariates									
Gender									
Male	**53.4**	49.8	47.5	**60.2**	**55.7**	49.3	37.1	39.2	50.0
Female	46.6	**50.2**	**52.5**	39.8	44.3	**50.7**	**63.0**	**60.8**	50.0
Age									
15-34	17.3	27.9	29.4	8.4	28.7	20.1	**49.8**	27.8	25.3
35-54	35.8	**42.9**	**40.2**	**46.5**	**44.2**	**43.9**	27.2	25.6	**38.9**
55+	**46.9**	29.2	30.4	45.1	27.1	36.1	23.1	**46.6**	35.8
Household type and individual position									
Single person	14.1	**55.9**	**51.1**	**33.6**	**54.0**	20.8	2.14	20.8	**31.5**
Single person with children	3.90	9.92	13.6	6.18	7.73	2.87	1.03	5.38	6.34
Partner with children	32.5	14.1	12.4	32.9	14.9	**35.4**	35.5	21.6	25.3
Partner without children	**39.4**	14.9	16.1	25.6	12.8	27.9	23.0	**33.2**	24.6
Child	8.01	3.95	4.31	0.47	6.44	8.52	**36.8**	16.1	9.74
Other	2.15	1.27	2.50	1.27	4.14	4.57	1.46	3.04	2.47
Education level									
None	2.49	7.90	5.20	3.96	10.1	5.52	2.19	0.00	4.82
Low	26.8	26.5	29.9	16.5	30.7	18.8	28.1	30.7	25.8
Intermediate	**40.2**	**31.7**	17.9	36.8	**36.7**	33.5	**34.5**	**43.3**	**34.2**
High	29.8	31.3	**39.1**	**39.3**	20.4	**39.3**	28.5	20.6	31.6
Other	0.80	2.56	7.83	3.44	2.20	2.91	6.66	5.41	3.64
Standardized disposable household income group									
First quintile (lowest)	**24.5**	**74.2**	**54.5**	**26.1**	**67.0**	**29.8**	**21.5**	**35.6**	**41.4**
Second quintile	16.4	8.80	14.1	17.3	14.0	17.0	19.1	19.1	15.4
Third quintile	15.1	3.70	7.05	17.1	8.83	22.8	19.3	19.7	13.7
Fourth quintile	18.7	1.70	3.42	22.2	2.53	11.2	16.4	16.4	11.7
Fifth quintile (highest)	24.1	3.05	7.13	16.5	2.13	18.8	18.9	8.60	13.3
Unknown	1.27	8.58	13.8	0.81	5.53	0.40	4.91	0.61	4.57
(Parental) birthplace									
The Netherlands	**78.2**	42.4	28.0	**69.1**	**58.6**	39.4	**51.5**	**86.5**	**56.5**
Outside the Netherlands	21.8	**57.6**	**72.0**	30.9	41.4	**60.6**	48.5	13.5	43.5
	%								
Inactive covariate									
Urbanization level residence									
Highly urbanized	2.17	21.5	**92.0**	26.2	10.3	**87.6**	25.5	0.00	32.5
Strongly urbanized	31.8	**53.6**	6.83	**47.7**	**40.8**	9.86	**53.6**	1.41	**32.6**
Moderately urbanized	24.3	17.4	1.10	17.4	11.7	2.27	11.9	0.78	13.0
Slightly urbanized	**32.5**	7.23	0.00	7.60	28.5	0.29	7.91	44.1	15.6
Non-urbanized	9.36	1.41	0.00	1.08	8.68	0.00	1.04	**46.7**	6.29

For categorical variables, the highest frequency within each cluster is put in bold face. For continuous variables, the highest mean value across all clusters is put in bold face.
* Defined by thousands of jobs based on log-logistic travel time decay function.
n = 1840 unemployed individuals.

licenses (93.6%), suggesting a strong reliance on personal vehicles for transportation. Group 1 exhibits low accessibility across all transport modes, with the second-lowest public transport accessibility (36.3 compared to the sample total of 150) and bike accessibility (19.1 compared to the sample total of 49.4), alongside below-average car accessibility (917 compared to the sample total of 1259).

Socio-demographically, there is a slight male majority (53.4%), and the group skews older, with 46.9% over the age of 55. In terms of household type, there is a prevalence of partners without children (39.4%) and those with children (32.5%), indicating established families and child-free or post-parenting stage partners. Education levels are varied, with a notable proportion having intermediate education (40.2%). Economically, a substantial segment falls within the highest household income quintile (24.1%), explaining the relatively high levels of car availability. The majority (78.2%) have a (parental) birthplace in the Netherlands. Urbanization levels are diverse, but a significant portion (32.5%) live in slightly urbanized areas, reinforcing the idea of suburban or semi-rural residences.

5.2.2. Group 2: medium accessibility, very low car availability (14%)

This cluster accounts for 13.7% of the sample and is marked by an absence of car ownership (100%). A majority do not possess a driver's license (58.4%), indicating a reliance on public or non-motorized forms of transportation. Group 2 has medium accessibility with public transport accessibility (128) and bike (41.3), and car accessibility (1430) being slightly above the sample total mean. The group has an even gender split, is relatively slightly young with a significant number aged 15-34 (27.9%), and tends to be single (55.9%). Educational levels are evenly distributed across low, intermediate, and high categories, suggesting a mix of backgrounds. However, a relatively very large portion of this group is in the lowest household income quintile (74.2%), which may reflect the young and single demographic and the low levels of car availability. Over half (57.6%) have a (parental) birthplace outside the Netherlands, and the majority are located in highly (21.5%) or strongly urbanized (53.6%) areas, aligning with inner-city living.

5.2.3. Group 3: very high accessibility, very low car availability (13%)

Making up 12.5% of the sample, individuals in this group also do not own cars (100%) and are less likely to have a driver's license (66.8%). They have the highest accessibility through public transport (385) and bike (121), far exceeding the sample total mean. The group is relatively balanced in terms of gender, slightly skewed towards females (52.5%), and is slightly younger than average (29.4% are 15-34). A plurality of the group is single (51.1%), and there is a considerable representation of high education (39.1%). This group is predominantly in the lower two household income quintiles, suggesting economic modesty. Most have a (parental) birthplace outside the Netherlands (72.0%), and an overwhelming majority reside in highly urbanized environments (92.0%), which aligns with the high accessibility through public transport and bike in such areas.

5.2.4. Group 4: medium accessibility, very high car availability (12%)

This cluster represents 12.3% of the sample and is characterized by universal car ownership (100%) and a high percentage of driver's license holders (97.7%). Group 4 has medium accessibility, with public transport accessibility (130) and bike accessibility (40.8) slightly below the sample total mean, whereas car accessibility (1453) is slightly above the sample total mean. This group has the largest proportion of males (60.2%) and is considerably old (only 8.4% aged 15-34). Partners with children (32.9%) and without children (25.6%) are common, pointing to traditional family structures. Although, a substantial portion of this group is single (33.6%). Education is skewed towards higher levels (39.3%). The group generally has relatively high household income levels, offering an explanation for their high car availability levels. The majority have a (parental) birthplace in the Netherlands (69.1%), and a substantial portion live in strongly urbanized areas (47.7%), suggesting suburban lifestyles with strong ties to city centers.

5.2.5. Group 5: very low accessibility, very low car availability (12%)

With 12.0% of the sample, almost all in this group do not own a car (98.9%), and a majority lack a driver's license (59.2%). Group 5 faces very low accessibility with the third-lowest access through public transport (36.4) and bike (21.7), along with the second-lowest car accessibility (495). Considering that both accessibility and car availability are relatively very low, this group could be at an exceptionally high risk of transport-related exclusion from out-of-home activities. The gender distribution is slightly male-dominated (55.7%), and there is a slightly younger age distribution. Single persons (54.0%) form the majority of this cluster, and education levels tend to be lower, with only 20.4% possessing a high level. Financially, the majority fall into the lowest household income quintile (67.0%), the second-highest share among all groups—corresponding with their very low car availability levels. Over half (58.6%) have a (parental) birthplace in the Netherlands. A considerable number live in strongly urbanized (40.8%) or slightly urbanized areas (28.5%), suggesting varied urban living conditions.

5.2.6. Group 6: very high accessibility, medium car availability (12%)

Accounting for 11.7% of the sample, this group balances car ownership (54.9%) with very high accessibility through public transport (342) and bikes (103). Gender is evenly split, and the group trends slightly middle-aged with a significant proportion aged 35-54 (43.9%). A large percentage of members are partners with children (35.4%). Educationally, there is a significant presence of high education (39.3%). Household income levels are generally somewhat higher, with a sizeable part in the highest household income group (18.8%). The majority have a (parental) birthplace outside the Netherlands (60.6%), and a notable majority reside in highly urbanized areas (87.6%), indicating an urban, family-oriented demographic.

5.2.7. Group 7: medium accessibility, medium car availability (11%)

Group 7, comprising 11.4% of the sample, is characterized by medium accessibility, with public transport accessibility at 141 and bike accessibility at 43, which is in line with the sample total mean. Interestingly, while the levels of car ownership (8.32%) and driver's license possession (52.7%) are low, indicating less individual control over private vehicles, there is a high number of cars in the household (60.2% have one car, and 39.0% have two or more). This discrepancy can be attributed to a substantial portion of this group being children living with their parents (36.8%), which may also explain the relatively lowest share of the lowest household income quintile (21.5%) among all groups. There is a female majority (63.0%), and the group has a high proportion of young adults (49.8% aged 15-34). Educational levels tend to be slightly lower, with intermediate education being the most common (34.5%). A considerable number have a (parental) birthplace in the Netherlands (51.5%), and many live in strongly urbanized areas (53.6%), suggesting a demographic that balances city living with the convenience of car use.

5.2.8. Group 8: very low accessibility, medium car availability (7%)

The smallest group at 6.7% of the sample, has very low accessibility, with the least access through public transport (9.94), bike (5.61), and car (450). However, there is some mitigation of transport disadvantage through car ownership (63.3% owning a car). There is a female majority (60.8%), and the age distribution is relatively old (46.6% over 55). Partners with children make up almost a third of the cluster (33.2%). Education levels are varied but tend toward intermediate (43.3%). The proportion of individuals within all three middle-household-income quintiles exceeds that of the overall sample. The majority have a (parental) birthplace in the Netherlands (86.5%), and a significant number live in non-urbanized (46.7%) or slightly urbanized areas (44.1%), indicating rural or peripheral urban areas where medium car availability could be necessary for daily activities.

5.3. Summary

This chapter lays the groundwork for subsequent in-depth analyses by establishing eight distinct clusters that define the transport accessibility, car availability, and socio-demographic contexts of unemployed individuals within varied urban settings. The LCCA employed here does more than just categorize; it enables a nuanced inquiry into the constraints on out-of-home activity participation for each identified group.

The analysis reveals a significant divide: low car availability clusters, representing 61% of the sample, predominantly comprise younger individuals in single-person households with lower household incomes, who have non-native (parental) birthplaces and reside in highly urbanized areas. These clusters, characterized by lower car availability and higher accessibility, illustrate the potential reliance on non-motorized travel modes and public transport, closely associated with their urban settings and socio-demographic factors. In contrast, the high car availability clusters, encompassing 39% of the sample, consist of older individuals with more favorable socio-demographic traits such as higher household incomes and support from multi-person households, residing in less urbanized areas where car ownership is crucial due to limited public transport and active mode accessibility.

The socio-demographic and urbanization profiles derived from this analysis are instrumental in understanding the degree to which transport resources empower or limit these individuals. By providing this foundational context, the chapter acts as a critical enabler for exploring the extent of transport-limited out-of-home activity participation, setting the stage for targeted interventions that can alleviate such limitations.

6

Transport-related activity exclusion

This chapter delves into the nuanced ways in which accessibility, car availability, socio-demographic characteristics, and residential urbanization levels collectively shape the out-of-home activity participation and travel behavior of unemployed individuals. The analysis brings to light the diverse strategies utilized by various groups to navigate their environments and participate in out-of-home activities. From the heavy reliance on personal vehicles in areas of limited accessibility to the utilization of public transportation systems in urbanized settings, each group's approach to overcoming their specific transport disadvantages reveals a narrative about the impact of transport disadvantage and unemployment on access to a wide variety of activities. This chapter aims to map these patterns and offer insights into the potential for compensatory behaviors regarding out-of-home activity participation that emerge in response to being unemployed in the face of differing transport-related limitations.

6.1. Out-of-home activity participation and travel behavior among the unemployed groups

As I explore the out-of-home activity participation and travel behavior among unemployed groups shown in Table 6.1, it's essential to recognize how accessibility, car availability, socio-demographic characteristics, and residential urbanization levels uniquely relate to these behavioral outcomes. Each group reveals a distinct interaction between all these factors, dictating their mobility patterns and their engagement with the surrounding environment. From individuals relying heavily on personal vehicles to navigate areas of low accessibility to those leveraging public transportation and biking within highly urbanized settings, the strategies adopted reflect both the limitations and adjustments made in response to their situations.

Additionally, the nature and frequency of activities engaged in shed light on how these groups find ways to connect with social and recreational opportunities or fulfill personal and family responsibilities. This section aims to dissect these interrelations, offering a detailed examination of how various groups address their mobility needs and participate in out-of-home activities.

Figure 6.1 is a pivotal element of my exploration into the travel behavior and activity participation of unemployed individuals, distinguishing between the red and green clusters. It reveals the extent to which car availability, accessibility, socio-demographics, and residential urbanization are connected to out-of-home activity participation and travel behavior.

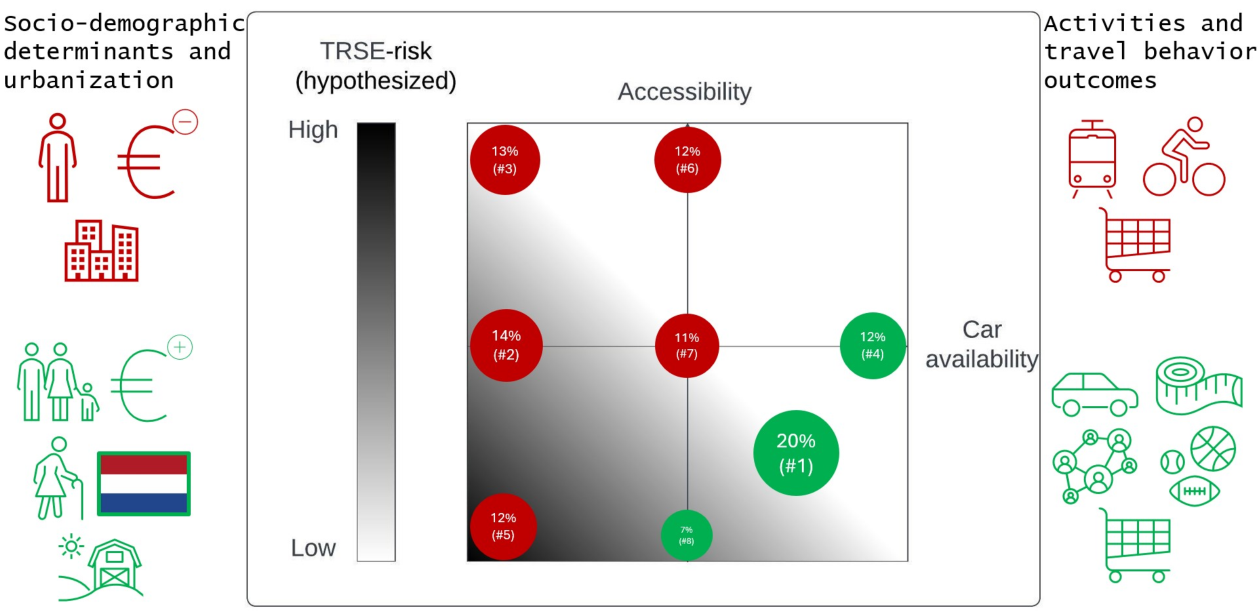


Figure 6.1: Mapping of each cluster onto the indicator-profiles-derived accessibility and car availability plane, with socio-demographic, residential urbanization level, activity participation, and travel behavior context.
Note: Clusters are visualized as circles sized proportionally to their sample size percentages, with numbers indicating their size ranking from largest (#1) to smallest (#8).

The red clusters depicted in Figure 6.1, comprising 61% of the unemployed sample, represent groups with limited car availability yet a higher degree of accessibility. These clusters frequently partake in routine activities such as grocery shopping. Following these groups' transport disadvantage profile, associated with urban residency, these individuals often rely on active forms of transportation such as walking and cycling, as well as public transport. This pattern extends beyond the simple availability of transport options, interweaving with socio-demographic dimensions; they are typically younger and contend with lower household incomes.

Contrastingly, the green clusters in Figure 6.1, representing 39% of the unemployed sample, indicate individuals with higher car availability, who typically partake in more and a broader spectrum of activities, including social, recreational, and transporting others or goods. They tend to have support structures of multi-person households, higher household income levels, and reside in less urbanized areas with lower accessibility, highlighting the importance of personal vehicles in their daily travel. Despite having a similar amount of daily travel time as those with lower car availability, these individuals exhibit greater daily travel distance.

I will now explore the specific travel behaviors and activity patterns within each cluster, looking to uncover how individuals with varying levels of car availability and accessibility, and from different urbanization settings navigate their environments and sustain their participation in a range of activities. This analysis aims to provide details on the complex dynamics of transport resources, urbanization, and socio-demographic characteristics in shaping travel behavior and out-of-home activity participation.

6.1.1. Group 1: low accessibility, high car availability (20%)

Group 1 exhibits relatively high out-of-home activity participation, significantly facilitated by their high car availability. This group's reliance on personal vehicles is evident in their travel behavior, including longer travel distances and times, likely due to their residing in slightly urbanized areas where destinations are more spread out. Their socio-demographic profile, primarily forming a partner household with or without children, combined with their residence in slightly urbanized areas, supports the notion that cars are not just a mode of transport but a necessity for maintaining social connections and fulfilling personal and family responsibilities.

6.1.2. Group 2: medium accessibility, very low car availability (14%)

Group 2 engages in a moderate level of out-of-home activities, with a slight discerning lean towards educational and work activities. Their urban living conditions, combined with medium accessibility, allow them to rely on public transportation and biking, aligning with the younger, predominantly single demographic's lifestyle and their low household income level. This group's activity participation reflects the urban infrastructure's ability to support diverse needs even with very low car availability.

Table 6.1: Within-cluster mean values of distal outcomes.

	Clusters: accessibility-car availability								
	1: low-high	2: medium-very low	3: very high-very low	4: medium-very high	5: very low-very low	6: very high-medium	7: medium-medium	8: very low-medium	Sample total
Cluster size	20%	14%	13%	12%	12%	12%	11%	7%	
Activity participation (number of out-of-home activities across all individuals)									
Total	**1.65**	1.33	1.13	1.53	1.18	1.33	1.11	1.51	1.36
Work	0.0985	**0.136**	0.0576	0.0888	0.135	0.0559	0.0377	0.120	0.0912
Business or occupational	0.0092	0.0031	0.0016	0.0001	**0.0137**	0.0019	0.0079	0.00	0.0052
Groceries or shopping	0.496	0.490	0.419	0.466	0.446	**0.509**	0.395	0.495	0.466
Transporting people or goods	**0.359**	0.161	0.0778	0.279	0.132	0.267	0.164	0.133	0.211
Education	0.0175	**0.0326**	0.0325	0.0279	0.0255	0.0275	0.029	0.0171	0.0261
Social visit	0.180	0.124	0.109	0.189	0.0888	0.110	0.126	**0.276**	0.146
Social and recreational other	0.224	0.205	0.242	0.229	0.114	0.185	0.231	**0.258**	0.209
Touring or hiking	0.153	0.0917	0.0633	0.143	**0.165**	0.104	0.0533	0.154	0.117
Services or personal care	**0.100**	0.0553	0.0895	0.0689	0.0381	0.0445	0.0602	0.0606	0.0678
Other	0.0164	0.0355	0.0347	**0.042**	0.0186	0.0224	0.0056	0.00	0.0231
Travel distance (in km)	28.2	18.6	15.0	**31.0**	19.1	21.8	16.0	26.8	22.3
Travel time (in minutes)	71.5	68.1	**72.0**	69.9	71.4	67.8	46.3	56.6	66.6
Travel period (number of trips across all individuals)									
Weekday									
Night (0:00-6:30)	0.0117	0.0007	0.0116	0.0003	0.00	0.001	0.0095	**0.013**	0.006
Morning peak (6:30-9:00)	**0.214**	0.183	0.106	0.198	0.152	0.179	0.178	0.173	0.176
Between peaks (9:00-16:00)	**1.43**	1.02	1.00	1.29	1.13	1.06	0.985	1.21	1.16
Afternoon peak (16:00-18:30)	0.323	0.297	**0.356**	0.346	0.207	0.353	0.151	0.277	0.293
Evening (18:30-23:59)	**0.294**	0.222	0.108	0.217	0.193	0.218	0.155	0.183	0.207
Weekend or national holiday									
Night (0:00-6:30)	0.0153	0.0033	0.0034	0.0048	0.00	0.011	0.0159	**0.0349**	0.0099
Day (6:30-18:30)	0.502	0.552	0.357	0.496	0.279	0.442	0.434	**0.622**	0.456
Evening (18:30-23:59)	0.123	0.0982	0.0947	0.0919	0.0853	0.0648	0.0746	**0.141**	0.0967
Mode usage (number of trips across all individuals)									
Public transport	0.0421	0.191	**0.263**	0.00	0.0819	0.231	0.116	0.045	0.120
Car (driver)	**1.404**	0.189	0.0043	1.401	0.170	0.817	0.484	1.19	0.726
Car (passenger)	0.259	0.232	0.130	0.110	0.205	0.203	0.343	**0.356**	0.224
Bike	0.688	**1.02**	0.750	0.649	0.688	0.446	0.494	0.502	0.673
Walk	0.488	0.655	**0.854**	0.455	0.634	0.634	0.527	0.559	0.596
Other	0.0313	0.103	0.0444	0.0397	**0.272**	0.0066	0.0471	0.0183	0.0707

n = 1840 unemployed individuals, one day of travel diary data per individual.
The highest mean value across all clusters is put in bold face.

6.1.3. Group 3: very high accessibility, very low car availability (13%)

Despite very high accessibility, Group 3 has one of the lowest totals for out-of-home activity participation. They primarily depend on public transport and walking, indicative of an efficient use of urban mobility options available in highly urbanized areas. The lower activity participation suggests that factors beyond transport accessibility, such as possibly limited opportunities or personal choice, play a role in the engagement levels of this relatively younger-aged, highly educated, and predominantly single group with an over-representation of (parental) birthplace outside the Netherlands.

6.1.4. Group 4: medium accessibility, very high car availability (12%)

Group 4's activity participation is strongly supported by their very high car availability. This group prefers using personal vehicles for a wide array of activities, indicative of a lifestyle where cars are central to daily routines. Residing in areas with medium accessibility, their demographic profile suggests a reliance on cars for both essential and discretionary activities. This group's profile—dominated by an older, male majority with predominantly traditional family structures—suggests that car ownership is closely tied to household responsibilities.

6.1.5. Group 5: very low accessibility, very low car availability (12%)

Group 5 faces relatively low activity participation levels, reflecting the compounded impact of very low accessibility and car availability. Their engagement in out-of-home activities is likely limited, highlighting the barriers faced in accessing services and social opportunities.

The socio-demographic composition, characterized by lower household incomes, and a younger age distribution, alongside the high proportion of singles, indicates a potentially vulnerable segment of the population. Residing mostly in strongly urbanized or slightly urbanized areas, their relatively low participation rates are particularly concerning, as it suggests that urban living conditions alone do not guarantee access to essential services and social opportunities, especially for those without personal vehicles or adequate transport accessibility levels.

6.1.6. Group 6: very high accessibility, medium car availability (12%)

Group 6 engages in activities primarily centered around groceries or shopping and transporting people or goods, indicating a focused use of their very high accessibility for essential tasks. Their level of total activity participation is average among unemployed groups, suggesting that while they have access to various transport modes, including public transport and biking, their out-of-home activities are more necessity-driven rather than leisure or social-engagement-focused. The group's balanced mobility approach, facilitated by medium car availability, supports their participation in these essential activities within highly urbanized environments.

The demographic composition of Group 6, with an even gender distribution, a significant representation of middle-aged individuals, a variety of family structures, and a generally high level of education, paints a picture of a highly educated diverse group. Their utilization of both public and private transport modes does not necessarily translate into a broad spectrum of out-of-home activities.

6.1.7. Group 7: medium accessibility, medium car availability (11%)

Group 7 stands out for its lowest total out-of-home activity participation across all unemployed groups, highlighting a comparatively low interaction with their environment. However, their participation in 'social and recreational other' activities is relatively higher, suggesting a selective approach to engaging in activities that offer social fulfillment and recreational value.

Despite their low activity participation, Group 7's balanced use of all transport modes showcases an effective adaptation to their circumstances, underpinned by medium accessibility and car availability. This mobility behavior aligns with their socio-demographic profile, characterized by a younger demographic—including a substantial number of children living with parents—that might be more open to and capable of leveraging diverse modes of transportation and have less personal car availability. Living in strongly urbanized areas, this group faces unique challenges and opportunities: while their environment theoretically offers abundant activity options, actual engagement is tempered by the realities of their accessibility and car availability situation.

6.1.8. Group 8: very low accessibility, medium car availability (7%)

Group 8's above-average activity participation is facilitated by medium car availability, mitigating the effects of very low accessibility. This group's reliance on cars enables access to essential services and social activities, critical in their non-urbanized or slightly urbanized areas where alternative transport options are limited.

Interestingly, Group 8's demographic profile, featuring a predominantly older, female population, and a notable number of partners without children, appears to align closely with their activity preferences. These characteristics suggest a group that not only values but actively seeks out social engagements and recreational activities, utilizing their available means of transport to ensure participation. This behavior highlights the adaptive strategies employed by Group 8 to maintain social connections and pursue leisure activities, reflecting a proactive approach to enhancing their social inclusion through social interactions.

6.2. Propensity score matching results

The propensity score matching process, pivotal in the comparative analysis of unemployed and employed individuals' out-of-home activity participation and travel behavior, has yielded exceptionally congruent matches across socio-demographic characteristics. As evidenced by Figure 6.2 and Figure 6.3, the propensity scores and covariates for almost all matched individuals fall well below the commonly used threshold of 0.1 for the standardized or binarized mean difference, indicating an exceptionally high degree of balance. These results indicate that the matching algorithm succeeded in pairing nearly all unemployed individuals with employed counterparts who share remarkably similar socio-demographic profiles.

This level of accuracy in matching is hardly surprising, given the substantial size of the employed group relative to the unemployed, which is more than twenty-eight-fold larger. Such a disparity in group sizes inherently increases the probability of identifying an employed individual who mirrors the socio-demographic attributes of each unemployed person. The one-to-one matching strategy capitalizes on this size difference, ensuring that for every unemployed individual, there exists a unique corresponding employed individual with nearly identical characteristics of gender, age, household type and individual position, education level, household income bracket, and birthplace.

According to the quality indicators of the propensity score matching process presented in Table 6.2, the mean propensity score differences between matched unemployed and employed individuals are minimal, with t-values close to zero and p-values nearing 1, underscoring a lack of significant differences in propensity scores post-matching as the zero hypothesis is no difference between the unemployed cluster and their socio-demographically matched employed counterparts.

Given these minute mean differences and high p-values, it is reasonable to infer that the discrepancies observed in out-of-home activity and travel behaviors are not a direct byproduct of differing socio-demographic backgrounds, at least not in terms of the variables included in the matching process. This reinforces the validity of subsequent analyses ex-

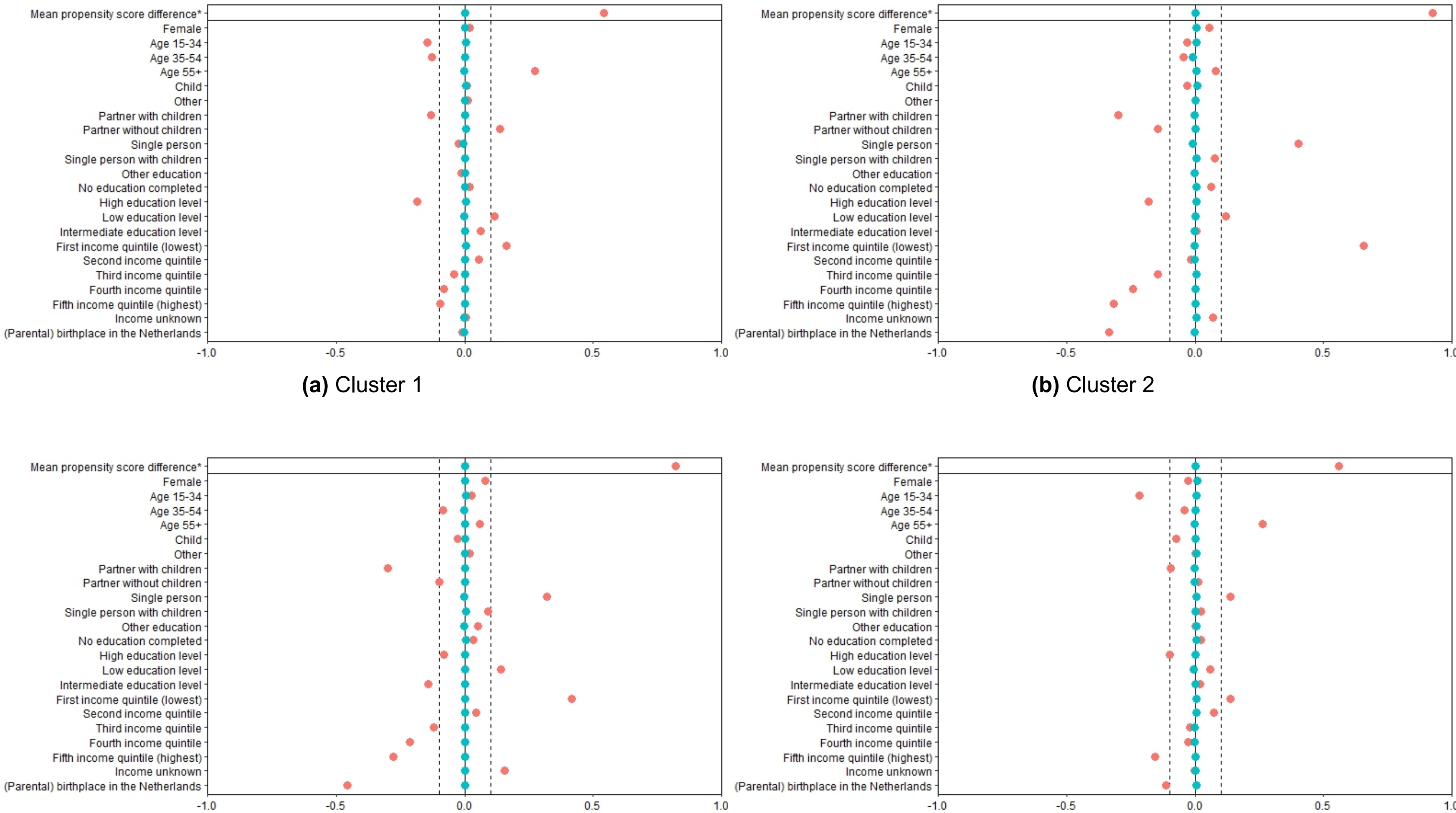
Table 6.2: Quality indicators of propensity score matching process.

Cluster	Matches	Unmatched	Mean propensity score difference*	t-value	p-value
1	391	1	-1.49e-07	-8.90e-05	0.99993
2	222	3	7.04e-07	1.06e-04	0.99992
3	228	3	7.74e-06	1.36e-03	0.99892
4	245	0	-1.10e-06	-7.75e-04	0.99938
5	168	2	2.39e-06	5.00e-04	0.99960
6	237	1	4.92e-06	1.94e-03	0.99845
7	208	1	3.69e-07	2.05e-04	0.99984
8	130	0	3.27e-06	1.73e-03	0.99862

*Between matched unemployed and employed.

ploring the impact of employment status and transport disadvantage on out-of-home activity participation and travel behavior, which rely on the assumption that matched individuals are comparable in all but their employment status and transport disadvantage.

The results of the propensity score matching thus establish a solid groundwork for delving deeper into the influences of unemployment, accessibility, and car availability on out-of-home activity participation and travel behavior. There is substantial assurance that the observed effects are distinctly attributed to these factors, unobscured by the socio-demographic variables accounted for in the matching process.



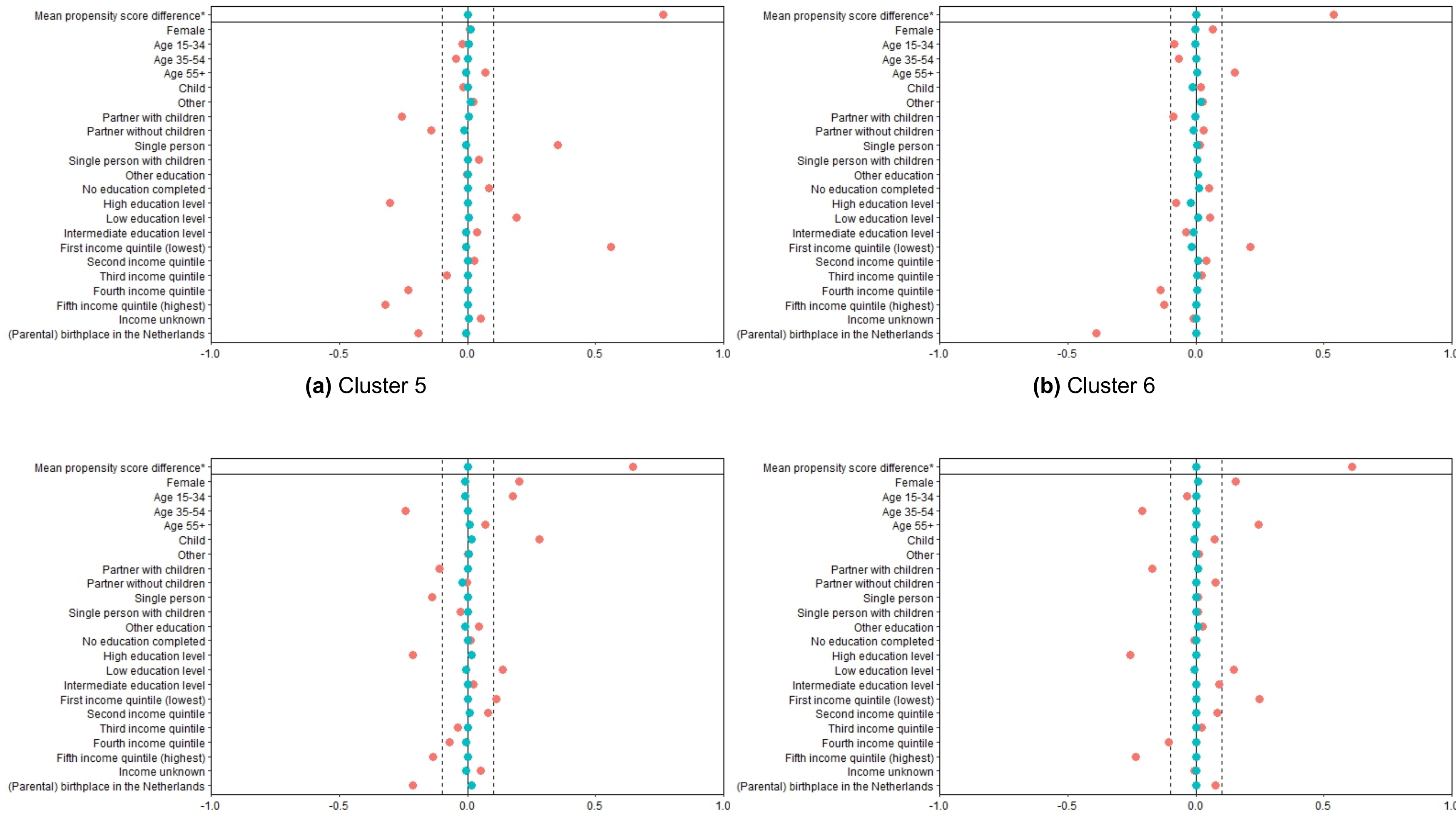
(a) Cluster 1

(b) Cluster 2

(c) Cluster 3

(d) Cluster 4

Figure 6.2: Mean differences in propensity score and binarized socio-demographic covariates between unemployed clusters 1 to 4, all employed (red dots), and respective employed control groups (blue dots).
**Standardized, no standardization required for the binarized covariates. n = 1840 unemployed individuals.*



(a) Cluster 5

(b) Cluster 6

(c) Cluster 7

(d) Cluster 8

Figure 6.3: Mean differences in propensity score and binarized socio-demographic covariates between unemployed clusters 5 to 8, all employed (red dots), and respective employed control groups (blue dots).
**Standardized, no standardization required for the binarized covariates. n = 1840 unemployed individuals.*

6.3. Impact of transport disadvantage on activity participation and travel behavior

The culminating analysis of this thesis scrutinizes the relationship between transport disadvantage patterns and deficits in out-of-home activities, as reflected in Table 6.3 and Table 6.4. The data generally indicates an absence of significant deficits in out-of-home activities due to employment status, accessibility, and car availability, aside from expected deficits in work-related activities.

The findings suggest that while work and business or occupational activities are understandably reduced for unemployed individuals, there is a prevalent trend of excess participation in other categories such as groceries or shopping, transporting people or goods, and touring or hiking. This observation points to a compensatory mechanism where individuals engage more in non-work-related trips, akin to the shift in travel patterns observed during the COVID-19 pandemic when restrictions on work-related travel led to an increase in other activities (Buitelaar et al., 2021).

However, this compensatory pattern does not uniformly manifest across all groups. Notably, groups 3 and 7 exhibit a significant deficit in total activity participation (at the 5% level), and similarly, groups 5 and 6 (at the 10% level), as well as group 2 to a lesser extent (at the 17% level), demonstrate significant deficits. These discrepancies suggest that car availability plays a more pivotal role than accessibility in enabling the full realization of this compensatory behavior because groups 1,4, and, 8—who enjoy higher levels of car availability despite lower accessibility—mostly realize the compensatory pattern. The type of activities where excesses occur among the high car availability groups tend to be related to household sustenance and recreation (groceries or shopping, transporting people or goods, and touring or hiking).

This finding contradicts the hypothesized compensatory relationship between transport accessibility and car availability, suggesting that individuals with greater car availability can offset their risk of transport-related social exclusion regardless of their accessibility level, whereas those with limited car availability are at a greater risk of exclusion, irrespective of their accessibility.

Remarkably, despite group 2 and group 3 both facing very low car availability and the latter enjoying significantly higher accessibility across all transport modes, group 2 has fewer deficits in out-of-home activities than group 3. This disparity arises despite the lower household incomes of group 2, hinting that higher deficits of group 3 may stem from the compounded challenges of unemployment coupled with a higher incidence of (parental) birthplaces outside the Netherlands. This combination likely exacerbates social exclusion for group 3, which could account for their significant deficit in social visits, indicating deeper issues of social integration and connectivity.

In terms of travel distances, all groups display significantly lower daily travel compared to their employed counterparts, with the reduction mainly attributable to the absence of work trips rather than a decrease in overall out-of-home activities as the high car availability groups with similar levels of total activity also exhibit significantly lower daily travel distances. This is further corroborated by the observation that lower travel times are less pronounced, suggesting that the unemployed generally undertake shorter trips.

When examining travel periods, a clear pattern emerges of unemployed individuals traveling more frequently outside of peak hours, aligning with non-work-related schedules. This pattern holds true across various levels of accessibility and car availability, affirming its link to employment status. However, some groups, particularly those with low car availability, show significant deficits in evening trips, highlighting the constraints faced when alternative transport options are less available or desirable.

Mode usage variations are also observed, with many excesses and deficits directly related to each group's specific transport accessibility and car availability profile. These differences show that factors beyond the socio-demographic covariates influence transport disadvantage patterns. As unemployed individuals are clustered based on transport disadvantage, and employed individuals are matched solely on socio-demographic similarity, discrepancies in transport disadvantage patterns between these employment-status-differentiated groups validate the research approach focused on transport-related barriers not resulting from socio-demographics such as transport and land use policies.

This analysis encapsulates the intricate effects of transport disadvantage on out-of-home activities among unemployed individuals in the Netherlands. It reveals that higher car availability typically facilitates out-of-home activity participation levels akin to those of the employed, underscoring the compensatory role of private vehicles. On the other hand, groups with low or modest car availability often experience substantial deficits in total out-of-home activity participation, even when displaying very high levels of public transport and bike accessibility. These findings highlight the critical role of car access in sustaining out-of-home activity participation for the unemployed, presumably significantly influencing their social inclusion.

Table 6.3: Average excesses in out-of-home activity participation and travel behavior of the unemployed compared to employed controls for clusters 1 to 4.

	Clusters: accessibility-car availability							
	1: low-high		2: medium-very low		3: very high-very low		4: medium-very high	
Cluster size	20%		14%		13%		12%	
	Excess	p-value	Excess	p-value	Excess	p-value	Excess	p-value
Activity participation (number of out-of-home activities across all individuals)								
Total	0.110	0.777	-0.185	0.165	**-0.478**	0.000	0.000	0.914
Work	**-0.399**	0.000	**-0.356**	0.000	**-0.386**	0.000	**-0.392**	0.000
Business or occupational	**-0.069**	0.000	**-0.063**	0.005	**-0.079**	0.000	**-0.090**	0.000
Groceries or shopping	**0.205**	0.000	**0.153**	0.010	0.035	0.681	**0.143**	0.035
Transporting people or goods	**0.220**	0.000	0.000	0.925	-0.022	0.636	**0.171**	0.005
Education	0.010	0.336	-0.041	0.148	-0.018	0.510	-0.004	0.803
Social visit	0.041	0.246	0.027	0.376	**-0.088**	0.027	0.057	0.219
Social and recreational other	0.031	0.559	0.032	0.741	0.035	0.468	0.020	0.636
Touring or hiking	0.028	0.330	**0.054**	0.042	0.018	0.453	**0.094**	0.008
Services or personal care	**0.049**	0.033	0.023	0.409	0.039	0.174	0.008	0.830
Other	-0.005	0.627	-0.014	0.592	-0.013	0.488	-0.008	0.674
Travel distance (in km)	**-15.468**	0.001	**-13.248**	0.000	**-23.963**	0.000	**-23.168**	0.000
Travel time (in minutes)	-5.043	0.113	-7.671	0.173	-10.311	0.301	-18.118	0.057
Travel period (number of trips across all individuals)								
Weekday								
Night (0:00-6:30)	**-0.028**	0.029	**-0.036**	0.013	**-0.039**	0.014	**-0.033**	0.037
Morning peak (6:30-9:00)	**-0.202**	0.000	**-0.216**	0.000	**-0.167**	0.000	**-0.135**	0.007
Between peaks (9:00-16:00)	**0.629**	0.000	0.185	0.115	0.140	0.198	**0.543**	0.000
Afternoon peak (16:00-18:30)	**-0.118**	0.007	**-0.189**	0.002	-0.114	0.062	**-0.167**	0.005
Evening (18:30-23:59)	-0.072	0.182	-0.099	0.119	**-0.364**	0.000	-0.094	0.184
Weekend or national holiday								
Night (0:00-6:30)	-0.013	0.266	-0.005	0.773	0.009	0.424	0.000	1.000
Day (6:30-18:30)	-0.023	0.601	0.036	0.632	-0.132	0.228	-0.086	0.582
Evening (18:30-23:59)	0.013	0.604	-0.014	0.683	-0.026	0.359	-0.053	0.222
Mode usage (number of trips across all individuals)								
Public transport	-0.049	0.107	-0.009	0.719	0.066	0.488	**-0.131**	0.000
Car (driver)	**0.353**	0.022	**-0.622**	0.000	**-0.882**	0.000	0.265	0.102
Car (passenger)	0.095	0.060	**0.135**	0.024	0.031	0.740	-0.012	0.834
Bike	-0.130	0.078	0.036	0.887	-0.123	0.366	-0.073	0.346
Walk	0.003	0.720	0.086	0.349	**0.246**	0.015	0.012	0.624
Other	**-0.115**	0.001	0.027	0.566	-0.053	0.154	**-0.114**	0.009

p-values from Wilcoxon signed-rank tests on socio-demographically matched pairs of individuals.
Bold face excesses indicate a significant difference at the 5% level, based on Wilcoxon signed-rank tests comparing socio-demographically matched pairs of unemployed and employed individuals.
n = 1840 unemployed individuals, one day of travel diary data per individual.

Table 6.4: Average excesses in out-of-home activity participation and travel behavior of the unemployed compared to employed controls for clusters 5 to 8.

	Clusters: accessibility-car availability							
	5: very low-very low		6: very high-medium		7: medium-medium		8: very low-medium	
Cluster size	12%		12%		11%		7%	
	Excess	p-value	Excess	p-value	Excess	p-value	Excess	p-value
Activity participation (number of out-of-home activities across all individuals)								
Total	-0.268	0.072	-0.257	0.089	**-0.269**	0.021	-0.092	0.678
Work	**-0.333**	0.000	**-0.447**	0.000	**-0.505**	0.000	**-0.431**	0.000
Business or occupational	**-0.065**	0.034	**-0.084**	0.002	-0.029	0.095	**-0.077**	0.010
Groceries or shopping	0.036	0.513	**0.169**	0.006	**0.197**	0.001	**0.177**	0.029
Transporting people or goods	0.024	0.897	0.042	0.386	0.053	0.345	0.077	0.115
Education	-0.006	0.790	0.004	0.824	**-0.067**	0.005	**-0.085**	0.024
Social visit	0.006	0.806	0.017	0.569	-0.038	0.368	0.085	0.188
Social and recreational other	0.006	0.878	-0.030	0.572	0.077	0.133	0.085	0.234
Touring or hiking	**0.113**	0.006	0.055	0.075	0.014	0.622	**0.123**	0.010
Services or personal care	-0.012	0.743	-0.008	0.728	0.029	0.167	-0.008	0.824
Other	-0.036	0.120	**0.025**	0.041	0.000	1.000	-0.038	0.089
Travel distance (in km)	**-17.205**	0.000	**-25.011**	0.000	**-23.671**	0.000	**-14.183**	0.042
Travel time (in minutes)	-10.673	0.111	-17.641	0.052	**-27.183**	0.000	**-15.238**	0.043
Travel period (number of trips across all individuals)								
Weekday								
Night (0:00-6:30)	**-0.054**	0.003	**-0.034**	0.013	**-0.043**	0.008	**-0.046**	0.041
Morning peak (6:30-9:00)	**-0.137**	0.013	**-0.241**	0.000	**-0.212**	0.001	**-0.238**	0.001
Between peaks (9:00-16:00)	0.250	0.057	**0.295**	0.017	**0.322**	0.013	0.262	0.183
Afternoon peak (16:00-18:30)	**-0.262**	0.001	**-0.203**	0.003	**-0.245**	0.000	**-0.246**	0.027
Evening (18:30-23:59)	**-0.137**	0.046	-0.051	0.480	**-0.212**	0.007	-0.038	0.572
Weekend or national holiday								
Night (0:00-6:30)	-0.018	0.149	0.013	0.233	-0.010	0.588	0.015	0.572
Day (6:30-18:30)	-0.161	0.205	-0.101	0.362	-0.024	0.670	0.108	0.467
Evening (18:30-23:59)	-0.012	0.785	-0.030	0.358	-0.014	0.648	0.023	0.716
Mode usage (number of trips across all individuals)								
Public transport	-0.113	0.056	-0.008	0.677	**-0.135**	0.045	**-0.223**	0.002
Car (driver)	**-0.571**	0.000	**-0.291**	0.040	**-0.312**	0.007	0.346	0.063
Car (passenger)	0.083	0.170	0.068	0.380	0.072	0.453	0.123	0.335
Bike	-0.149	0.371	-0.190	0.150	-0.236	0.068	**-0.362**	0.025
Walk	0.113	0.258	**0.207**	0.034	0.188	0.130	0.069	0.990
Other	0.071	0.669	**-0.152**	0.001	-0.043	0.395	**-0.162**	0.010

p-values from Wilcoxon signed-rank tests on socio-demographically matched pairs of individuals.
Bold face excesses indicate a significant difference at the 5% level, based on Wilcoxon signed-rank tests comparing socio-demographically matched pairs of unemployed and employed individuals.
n = 1840 unemployed individuals, one day of travel diary data per individual.

7

Discussion and conclusion

This chapter synthesizes the findings, implications, limitations, and resulting recommendations of an investigation into the disparities in transport accessibility and car availability among unemployed individuals in the Netherlands, framing these disparities within the broader contexts of socio-demographic factors, residential urbanization, and their collective impact on out-of-home activity participation and travel behavior. Through a meticulous categorization of unemployed individuals into eight distinct groups mainly based on transport accessibility and car availability, this study illuminates the nuanced ways in which these transport disadvantage aspects intersect with socio-demographic characteristics to influence the engagement of these individuals in various out-of-home activities such as shopping or groceries, social visits, and recreational activities.

Notably, the research uncovers a compensatory mechanism among the unemployed, highlighting their higher participation rates in non-work-related activities compared with socio-demographically similar employed individuals. However, the extent of this compensatory behavior is uneven across groups, particularly affected by car availability and socio-demographic disadvantages, thereby shedding light on significant disparities in social inclusion.

7.1. Main findings

This research unveils significant disparities in transport accessibility and car availability among unemployed individuals in the Netherlands, categorizing them into eight distinct groups. These groups are largely differentiated based on their access to jobs through various modes of transport (car, public transport, and bike) and levels of car availability (including personal car ownership, driver's license possession, and household car ownership).

This study identifies key socio-demographic factors (gender, age, household composition, education, income, and (parental) birthplace) that influence these patterns. Moreover, it explores the correlation between these factors and residential urbanization, offering insight into the spatial dimension of transport disadvantage.

Among the eight groups analyzed, there exists a complete spectrum of prevalent patterns concerning transport accessibility and car availability combinations, ranging from low to medium to high. However, a scenario where both car availability and accessibility are concurrently high is notably absent from the observed patterns. Some groups, particularly those with lower car availability, enjoy high accessibility, primarily facilitated through public transportation and biking in highly urbanized areas. Another segment, characterized by medium accessibility, exhibits greater car availability and tends to reside in strongly urbanized settings. Additionally, certain subsets of unemployed individuals experience low accessibility, typically in less urbanized residential areas, where high car ownership is observed and almost indispensable for daily access. Furthermore, the analysis highlights a distinct group facing compounded transport challenges, marked by both low car availability and low accessibility, despite their predominant residence in strongly or highly urbanized areas, underscoring a profound transport disadvantage.

Addressing the nuances of transport-related limitations in out-of-home activity participation, this research further investigates the eight unemployed groups. By examining their engagement in different activities and their travel behavior—including mode usage, travel period, daily travel time, and daily travel distance—it provides a granular view of how transport accessibility, car availability, socio-demographic characteristics, and residential urbanization, intersect with individuals' participation in out-of-home activities.

A comparative analysis, between the unemployed and their socio-demographically similar employed counterparts, reveals a compensatory mechanism among unemployed individuals, who tend to increase participation in non-work-related activities such as shopping, transporting people or goods, and recreation.

However, this trend of compensatory activity participation is not uniformly observed across all groups. Particularly, individuals with lower levels of car availability (five out of the eight identified groups, comprising 61% of the unemployed sample) engage less in such activities, irrespective of their varying but generally higher level of accessibility. These lower car availability groups typically consist of younger individuals with lower household income levels, single-person households, those with a (parental) birthplace outside the Netherlands, and residents of strongly or highly urbanized areas. These socio-demographic characteristics, often associated with social disadvantage, presumably further exacerbate the transport disadvantage challenges faced by these unemployed individuals.

In contrast, three out of the eight identified groups, comprising 39% of the unemployed sample, have relatively high car availability and low accessibility. These groups of individuals often reside in less urbanized areas and benefit from favorable socio-demographic conditions such as higher household incomes, multi-person households, and native (parental) birthplace status. These generally older individuals demonstrate a higher engagement in a wider array of activities and make use of personal vehicles to travel longer distances with similar travel times as those with lower car availability, fully realizing the compensatory mechanism by partaking in a comparable number of total activities relative to their socio-demographically-alike employed counterparts.

These observations challenge the initially hypothesized compensatory relationship between transport accessibility and car availability. It suggests that individuals with higher car availability are able to mitigate their risk of transport-related social exclusion effectively, regardless of their accessibility level. Conversely, those with limited car availability face a heightened risk of exclusion, which remains significant irrespective of their accessibility.

Regardless of car availability, groceries or shopping is the most frequent activity among all groups of unemployed individuals. However, those with higher car availability typically engage substantially more in social, recreational, and transporting people or goods activities compared with the low car availability unemployed, highlighting the impact of vehicle access on the type and number of out-of-home activities pursued.

The study finds that unemployed individuals with low car availability predominantly depend on walking or biking for transportation, and to a lesser extent, utilize public transport—reflecting not just transport disadvantage, but also closely associated with an over-representation of younger individuals, lower household incomes, single-person households, and residences in highly urbanized areas. Furthermore, a marked deficit in evening travel highlights their constrained mobility when their available modes of transport become less accessible or desirable.

This detailed exploration into the travel behaviors and out-of-home activity participation of unemployed individuals underscores the critical interplay between socio-demographic factors, transport disadvantage, residential urbanization, travel behavior, and out-of-home activity participation, offering valuable insights for targeting interventions to improve access and participation across these diverse groups.

7.2. Scientific implications

This research contributes to a nuanced understanding of the relationship between transport disadvantage and activity participation among unemployed individuals, addressing a significant gap in the existing literature. Prior studies have elucidated the vicious cycle connecting labor market marginality, poverty, and social isolation (Gallie et al., 2003), and recognized transport's pivotal role in mitigating social exclusion (Allen & Farber, 2020; Church et al., 2000; Currie et al., 2010; Lucas, 2012; Luz & Portugal, 2022; Yigitcanlar et al., 2019) and improving labor market outcomes (Bastiaanssen, 2012, 2020; Korsu & Wenglenski, 2010). Despite the acknowledged potential of transport and land use policies to counter social isolation, the specific impact of transport disadvantage on participation in non-labor-market activities among the unemployed had not been investigated before. This study bridges this gap, offering critical insights into the dynamics of transport and social marginalization within the TRSE field.

The pivotal finding of this research is the identification of a compensatory mechanism among unemployed individuals, who increase their participation in non-work-related activities such as shopping, transporting people or goods, and recreation. This insight originates from a comparative analysis of out-of-home activity participation between the unemployed and their socio-demographically similar employed peers. However, the findings suggest that limited car availability hinders the full realization of this compensatory mechanism, preventing unemployed individuals from achieving an equal amount of total out-of-home activity participation as their employed counterparts. Notably, high accessibility through public transport or bike does not necessarily facilitate this compensatory behavior. This unique contribution aligns with, yet distinctively expands upon, existing research that identifies car availability as the primary determinant of transport disadvantage (Gao et al., 2022; Lucas, 2012; Martens et al., 2019; Mattioli, 2021).

The observed compensatory behavior of increasing participation in non-work-related activities among the unemployed mirrors findings from other studies. For instance, Kunze & Suppa (2017) note similar trends where unemployment leads to increased engagement in activities like volunteering as substitutes for formal employment. This pattern is also reflected in shifts in out-of-home activity participation among Dutch travelers during the COVID-19 pandemic. Here, restrictions on work-related activities spurred an increase in participation in other activities (Buitelaar et al., 2021). This parallel suggests a broader, possibly universal, response to disruptions in regular employment routines, whether due to economic conditions or extraordinary societal changes.

The findings that younger individuals and single-person households exhibit lower car availability are consistent with existing research. For instance, Jorritsma & Berveling (2014) indicate a preference for bicycles and public transport over cars among Dutch young adults. Additionally, Maltha et al. (2017) demonstrate a positive correlation between household size and car ownership, suggesting that larger households are more likely to own cars.

Contrasting with findings from Luz et al. (2022) in Sao Paulo, Brazil, where limited accessibility restricts low-income individuals' engagement in discretionary activities, this thesis highlights that accessibility alone cannot overcome the limitations on activity participation due to low car availability.

It's crucial to recognize that not only limited accessibility but also limited affordability restrict engagement in out-of-home activities, particularly among lower-income groups with less car availability (Allen & Farber, 2020; Lucas et al., 2016; Ward & Walsh, 2023). While this study compares out-of-home activity participation between unemployed and employed individuals within the same household income quintile, the financial insecurity associated with unemployment, compounded by low household income, likely exacerbates the unaffordability of public transport.

Moreover, it is presumed that this compounded effect could be further intensified by additional social disadvantage factors, which are notably overrepresented among low household income and low car availability unemployed groups. These factors include the lack of supportive partnerships (Pohlan, 2019) and discrimination based on social attributes such as national identity, race, or ethnicity (Benevenuto & Caulfield, 2019). Such conditions presumably contribute to the reduced out-of-home activity participation observed within these groups.

In summary, this research significantly advances our understanding of how transport disadvantage among unemployed individuals affects their social participation. It does so by showing the complexity of the interplay between socio-demographic factors, transport disadvantage, residential urbanization, travel behavior, and out-of-home activity participation.

7.3. Policy implications

The findings of this research hold profound implications for policy development, particularly in the realms of transport, urban planning, and social welfare. By identifying and analyzing the intricate dynamics of transport accessibility, car availability, and their impacts on the out-of-home activity participation of unemployed individuals, this study provides a solid foundation for crafting targeted interventions aimed at mitigating transport disadvantage and fostering greater social inclusion.

Together with insights from the TRSE literature, this study highlights the significant impact of economic constraints on transport accessibility among unemployed individuals. Implementing subsidized transport schemes or providing travel allowances for low-household-income and unemployed individuals can alleviate these constraints, enabling access to out-of-home activities that are beyond the reach of walking and cycling. Such measures could help counter the limitations in activity participation due to financial insecurity and the unaffordability of public transport.

Affordability may also be enhanced by integrating urban and transport planning through mixed-use development. By guaranteeing or promoting mixed-use developments, policy-makers can increase the range of activities within reach of walking and cycling, which is crucial for the large subset of unemployed individuals with low car availability and limited financial means. Additionally, improving active mode infrastructure can ensure equitable access to services and amenities in urbanized areas, thereby significantly boosting possibilities for out-of-home activity participation among these individuals.

Finally, the identified socio-demographic determinants of transport disadvantage suggest the need for targeted support measures. Policies should be designed with a keen understanding of the specific needs of unemployed younger individuals, single-person households, lower-income households, and those with a (parental) birthplace outside the Netherlands. Tailoring interventions to these groups' unique circumstances can more effectively address the compounded effects of socio-demographic and transport disadvantages. A specifically tailored initiative that could be effective is community engagement programs that actively involve residents in planning and feedback processes. This ensures that development efforts are closely aligned with the community's needs, fostering greater inclusion and accessibility.

7.4. Study limitations

This research, while providing valuable insights into the interplay between transport accessibility, car availability, and activity participation among unemployed individuals, acknowledges several limitations.

Firstly, out-of-home activity participation is employed as a surrogate for social inclusion. This approach does not account for the possibility that unemployed individuals might engage in meaningful activities from home, either through physical visits (e.g., for educational, social, or recreational purposes) or digital interactions, which offer a vast array of activity options. Consequently, this measure may not fully capture the breadth of social inclusion experiences.

Moreover, social inclusivity encompasses subjective dimensions such as feelings of isolation that affect mental health outcomes, as well as the quality of interpersonal relationships. These critical aspects of social inclusion cannot be adequately captured through the lens of out-of-home activity participation alone, pointing to a gap in the study's ability to fully assess social inclusion.

The consideration of transport affordability in this study is also somewhat limited. While standardized disposable household income levels and employment status were incorporated in the study design, travel and housing expenses were not accounted for. Housing expenses are relevant because economically disadvantaged individuals have been shown to balance transport accessibility and car availability with housing expenses (Mattioli, 2017). Travel expenses can vary significantly depending on the transport accessibility from one's residential location to the desired activity locations, potentially impacting the affordability of participating in out-of-home activities.

Moreover, this study was unable to incorporate key confounding variables such as unemployment duration and health status in the quasi-experimental setting using propensity score matching, due to methodological constraints and data limitations. Notably, the control group, composed exclusively of employed individuals, precludes the inclusion of unemployment duration as a variable. Factors like the length of unemployment and an individual's health not only affect their likelihood of securing new employment but also their capacity to engage in activities outside the home. The omission of these variables could restrict the thoroughness of the results, especially in fully assessing how employment status and transport disadvantage impact participation in out-of-home activities.

An additional limitation of this study arises from the use of LCCA to identify distinct groups mainly based on transport accessibility and car availability. While LCCA is instrumental in uncovering hidden patterns and heterogeneity within complex data sets, it inherently faces challenges in clearly separating individuals into distinct groups. A significant limitation is that individuals may show substantial probabilities of belonging to multiple clusters, rather than a clear affiliation to a single cluster. This overlap can lead to ambiguities in defining group boundaries and dilutes the distinctiveness of identified group characterizations.

Lastly, it remains uncertain whether the compensatory mechanism of increased non-work-related activity participation observed among groups with higher car availability would manifest to the same extent among unemployed individuals with low car availability, should transport become more affordable. The study conjectures that the realization of such a compensatory mechanism might also be influenced by factors beyond transport and economic means, such as being in a supportive partnership and the degree of social inclusion derived from other sources (e.g., having a native (parental) birthplace).

These factors not only potentially provide groups with higher car availability—typically forming multi-person households and having a native (parental) birthplace—with opportunities to compensate by engaging in activities such as transporting people or goods, grocery shopping, or making social visits, but also potentially shape the very activities they desire to participate in. This underscores a multifaceted interaction between socio-demographic characteristics and transport-related factors, intricately influencing both out-of-home activity participation and the preferences for specific activities.

7.5. Recommendations for future research

Building on the insights and limitations identified in this study, several avenues for future research emerge. These recommendations aim to deepen our understanding of the nexus between transport accessibility, car availability, social inclusion, and the socio-economic impacts on unemployed individuals.

Future studies should expand the scope of investigation to include in-home activities, acknowledging their potential to contribute to social inclusion. Research could explore the nature and impact of activities conducted at home, whether through physical visits or digital interactions, to offer a more comprehensive understanding of social inclusion among the unemployed. This exploration would address the current study's limitation in capturing the full spectrum of social participation.

Given the complex and subjective nature of social inclusion, further research is needed to explore individuals' perceptions of isolation, mental health outcomes, and the quality of interpersonal relationships. Qualitative studies, in particular, could provide deeper insights into the subjective experiences of social inclusion and exclusion among unemployed individuals, complementing the quantitative measures of out-of-home activity participation.

Acknowledging the limited consideration of transport affordability in this study, future research should explicitly incorporate travel and housing expenses into the analysis. This could involve developing models that account for the variability in travel and housing costs related to car availability, residential accessibility, and the location of desired activities, thereby offering a more nuanced understanding of the economic barriers to social participation.

The observed extent of the compensatory mechanism of increased participation in non-work-related activity participation among groups with higher car availability raises questions about its applicability to those with lower car availability. Future research could investigate how this mechanism operates when transport becomes more affordable, and if this also depends on accessibility and car availability. This inquiry should consider additional factors such as age, household composition, and social networks that may influence the ability and desire to engage in various activities.

Furthermore, future studies could benefit from employing instrumental variable analysis or utilizing a natural experiment to address potential unobserved confounders that were not accounted for in this study, such as unemployment duration and health status. A promising candidate for an instrumental variable might be regional transportation policy changes. This could include the introduction or modification of public transport routes, or parking regulations that influence car ownership. These changes affect transport accessibility or car availability due to altered travel times or car ownership, without directly impacting individuals' decisions regarding their participation in various activities. By utilizing such instruments, researchers can strengthen causal inferences and provide more robust policy recommendations, enhancing the understanding of how transport disadvantage impacts out-of-home activity participation.

Future research should consider incorporating analytical methods other than LCCA to enhance the robustness and clarity of findings related to transport disadvantage and activity participation among the unemployed. Methods such as hierarchical clustering or K-means clustering could be employed to compare and contrast with the results obtained from LCCA. These methods offer different strengths in terms of defining clear group boundaries and might provide more distinct categorization of individuals based on their transport accessibility and car availability. Furthermore, advanced statistical techniques like structural equation modeling could be used to examine the direct and indirect relationships between socio-demographic variables, transport disadvantage, and activity participation. Structural equation modeling would allow for a more detailed exploration of the causal pathways and interactions among the variables, providing deeper insights into the complex dynamics at play.

Furthermore, the findings from this research underscore the need for panel studies to assess the effects of transport accessibility and affordability on social inclusion. Such studies would offer valuable insights into the temporal dynamics of unemployment, transport disadvantage, and social participation over time, informing the development and refinement of policy interventions aimed at improving the social inclusion of unemployed individuals.

Finally, future research should adopt an interdisciplinary approach, integrating insights from transportation, urban planning, sociology, psychology, and economics. This would facilitate a more holistic understanding of the factors influencing social inclusion and the role of transport in mitigating or exacerbating social exclusion among unemployed individuals. By bridging these disciplinary gaps, researchers can contribute to the formulation of comprehensive strategies that address the multifaceted challenges faced by the unemployed.

These recommendations set the stage for a more complete examination of the relationships between transport disadvantage, employment status, and social inclusion, aiming to generate more actionable insights for policymakers, urban planners, and social service providers.

7.6. Concluding remarks

This study has unearthed significant disparities in transport accessibility and car availability among unemployed individuals in the Netherlands, shedding light on how these elements interact with socio-demographic characteristics and residential urbanization to affect participation in out-of-home activities and travel behavior. The characterization of eight distinct groups based on all these factors underscores the varied experiences of the unemployed, with 61% of them experiencing substantial deficits in total out-of-home activity participation compared with socio-demographically-alike employed peers.

The key finding from this research is the compensatory mechanism among the unemployed, who tend to increase their participation in non-work-related activities such as shopping, transporting people or goods, and recreation. However, this compensatory behavior is not uniform across all groups. Particularly, those with lower levels of car availability—representing 61% of the unemployed—do not engage in as many out-of-home activities as their employed counterparts with similar socio-demographic profiles. This discrepancy, primarily due to limited car availability, challenges the hypothesized compensatory relationship, indicating that public transport or cycling options, even in highly accessible areas, are insufficient to mitigate the disadvantages of low car availability.

Additionally, the low car availability groups typically consist of those in single-person households, with lower household income levels, and a non-native (parental) birthplace, often residing in highly urbanized areas. These socio-demographic characteristics, associated with social disadvantage, likely further exacerbate the limited out-of-home activity participation among these unemployed individuals. The findings suggest a significant impact of low car availability and social disadvantage factors, compounded by unemployment, on limited participation in out-of-home activities.

Reflecting on these findings and drawing on existing literature that highlights how limited affordability can restrict engagement in out-of-home activities, several policy recommendations emerge to facilitate affordable access for the low car availability groups. To increase the range of activities within reach of walking and cycling, policymakers can promote mixed-use developments or enhance active mode transport infrastructure. Additionally, improving public transport affordability through subsidized fares can extend access to activities beyond walking and cycling distances, thereby also enabling fuller participation in out-of-home activities.

In response to the findings and limitations of this study, future research should focus on expanding the investigation to include in-home and digital activities to provide a comprehensive view of activity participation. Additionally, incorporating travel and housing expenses into the analysis would offer deeper insights into the economic barriers to out-of-home activity participation. Qualitative studies exploring the subjective experiences of social inclusion, such as perceptions of isolation and interpersonal relationships, are also crucial to providing a richer understanding of social inclusion. Employing instrumental variable analysis or utilizing natural experiments could strengthen causal inferences regarding the impacts of transport disadvantage and transport affordability on out-of-home activity participation, thus ensuring more targeted and effective policy measures. Finally, to enhance the distinctiveness in group characterization and improve the inference of causal relationships within the findings, it is recommended to utilize alternative analytical methods such as hierarchical clustering, K-means clustering, and structural equation modeling.

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