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Revealing accessibility disparities: A latent class analysis linking objective and subjective accessibility measures

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A B S T R A C T

The last decade denoted a growing interest in perceived accessibility, yet the link between perceived and objective accessibility measures is understudied. This paper aims to address accessibility poverty by identifying groups with different levels of perceived accessibility. To achieve this aim, we develop a latent class model that relates perceived accessibility patterns to social, transport, and geographical conditions encountered by individuals. To support the specification of the latent class model, we develop a theoretical framework that links transport, social, and geographical conditions with perceived inaccessibility. Data is obtained from the Dutch National Travel Survey, which includes information on travel patterns and preferences. In total, 20,020 participants are included in the analysis. The latent class model identified six social groups with varying levels of perceived accessibility. Notably, while 89% of the individuals perceive excellent accessibility, a minority of 11% experiences different forms of inaccessibility. In addition, the latent class model showed that social rather than transport or spatial conditions encountered by individuals determine perceived inaccessibility. The results lend support to tailored policies aimed at reducing accessibility poverty and social exclusion for specific segments of the population.

1. Introduction

Transport plays a fundamental role in providing individuals the opportunity to participate in social and economic activities. The UK Social Exclusion Unit study in 2003 underlined how poor transport contributes to social exclusion by restricting access to life-enhancing opportunities such as education and employment (Social Exclusion Unit, 2003; Lucas, 2012; Levine et al., 2019). As a result, policymakers and researchers are increasingly advocating for justly distributed access to opportunity in transport policies to leave no one behind (Martens, 2017; Levine et al., 2019).

Addressing justice in transport policies requires consensus on what constitutes social exclusion and how to measure it. While it is widely acknowledged that social exclusion is a multi-dimensional problem, a common understanding on social exclusion is lacking (Lucas, 2012). Definitions often differ with regard to their scope. Whereas some focus more on the individual itself (e.g. Burchardt et al., 1999, p. 229), others relate the individual's level of participation to the majority of society (e.g. Levitas et al., 2007, p. 25). While both Burchardt et al. (1999) and Levitas et al. (2007) conclude that an individual's level of participation determines whether he or she is socially excluded, Levitas et al. (2007) emphasize that an individual's level of participation cannot be considered in isolation. To assess whether an individual is socially excluded depends on the level of participation of this individual with that of the majority. In

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terms of transport, socially excluded individuals should have lower accessibility levels compared to the majority, a condition termed accessibility poverty (Martens and Bastiaanssen, 2019).

While accessibility poverty and social exclusion lurks for people with a lower level of accessibility compared to the majority, it is difficult to assess when these levels are insufficiënt. When an individual makes the voluntary choice to comply with lower levels of accessibility or participation, these lower levels may not be indicative for social exclusion (Van Wee and Geurs, 2011). Contrary, individuals with the highest levels of accessibility might still perceive limited access to opportunity, leading to perceived social exclusion. As such, it is crucial that both objective and subjective measures are studied simultaneously.

Recent studies have started to explore the link between objective and subjective accessibility measures. Objective accessibility measures often reflect one of the four components of accessibility as distinguished by Geurs and Van Wee (2004). These are the land-use, transportation, temporal, and individual components. The land-use component focuses on the accessibility level of specific geographical areas, whereas the transportation component studies the performance of transport infrastructure. The individual component analyses whether an individual can participate in activities. Yet, objective accessibility measures are limited in two ways. These measures are not able to capture the perceptions of individuals and to capture differences between individuals living in the same geographical area (Lättman et al., 2018). In contrast to objective measures, subjective evaluations are able to assess the level of accessibility from the individual's perspective (Curl, 2018). While recent research has suggested that objective and subjective evaluations systematically differ in outcome (Lättman et al., 2018; Pot et al., 2021), Pot et al. (2021) advocated that these differences do not imply that subjective accessibility evaluations are limited. Nonetheless, as underlined by Curl (2018), the reasons why a subjective evaluation differs from an objective evaluation should be addressed thoroughly.

Overall, few studies have examined the heterogeneity in perceived accessibility and systematically linked perceived accessibility with objective accessibility measures. Lättman et al. (2018); Lättman et al. (2020) evaluated differences in perceived accessibility between residential areas and travel modes. Contrary, Azmoodeh et al. (2023) identified the accessibility levels for low-capability and high-capability respondents. Whereas Van der Vlugt et al. (2022) revealed heterogeneity in walking accessibility, Pot et al. (2023b) evaluated the difference in accessibility levels for rural and urban areas. These studies all use observed variables related to the social, transport, and geographical aspects encountered by disadvantaged individuals to reveal heterogeneity in the perceived accessibility by individuals. However, identifying groups by relating different perceived accessibility patterns that emerge from the data to social, transport, and geographical aspects is not yet explored.

This paper aims to identify groups with different levels of perceived accessibility by relating perceived accessibility patterns to social, transport, and geographical conditions which often determine lower accessibility. To achieve this aim, a latent class model is developed. To support the specification of the latent class model, we develop a theoretical framework that links transport, social, and geographical conditions with perceived inaccessibility. Data is retrieved from the Dutch National Travel Survey (ODiN). This survey provides information on daily travel patterns and preferences, and is administered among a representative sample of the Dutch population. In total, 20,020 participants are included in the analysis.

This paper is structured as follows. Section 2 presents a literature review on studies centred around perceived accessibility, whereas Section 3 proposes the Accessibility Poverty Framework. Section 4 presents the methods used for the latent class analysis, whereas Section 5 formulates the model findings. Section 6 presents a discussion of the results in light of earlier findings and reflects on the latent class model specification. Lastly, Section 7 presents the conclusions drawn from the model findings, provides policy implications, and presents recommendations for future research.

2. Literature review

The last decade denoted a growing interest in perceived accessibility and its measures. As one of the first, Van Wee (2016) opted the perception of individuals on the accessibility of activities or locations as a measure for perceived accessibility. Afterwards, more advanced measures were proposed (e.g. Lättman et al., 2016; Lättman et al., 2018). In addition, a relatively large body of research focused on the drivers behind perceived inaccessibility. Often, these studies focus on individual, transport, and/or geographical aspects encountered by disadvantaged individuals. Consequently, this review clustered studies accordingly.

First, various studies focussed on transport aspects encountered by disadvantaged individuals. Often, these studies evaluate the perceived accessibility of a certain mode. For instance, Olfindo (2021) examined satisfaction with bus stop accessibilities. Wang et al. (2022a), Rossi et al. (2023), and Watthanaklang et al. (2024) all studied the perceived accessibility of regional public transport. Tiznado-Aitken et al. (2020), Tiznado-Aitken et al. (2021) and Ayuriany et al. (2023) narrowed down to public transport too yet conducted focus group discussions instead of a quantitative analysis. Rather than focusing on one mode, Fu et al. (2024) studied the relationship between multimodality and perceived accessibility. Another approach is taken by Chen et al. (2022), who focused on the perception of individuals on three transport disadvantages, namely: high costs or efforts, limited physical abilities, and opportunity inaccessibility.

Second, social aspects of disadvantaged individuals in relation to perceived accessibility have received attention too. Commonly, these studies focus on a certain group of people who may experience lower levels of accessibility. For instance, both Smale et al. (2022) and Lättman et al. (2023) studied the perceived accessibility among elderly people. Other studies focus on, among others, low-income communities (see Guimarães et al., 2019), individuals with inabilities (see Márquez et al., 2019), individuals with various digital skills (see Liu et al., 2021), and mentally ill people (see Friman and Olsson, 2023). Contrary, Ward and Walsh (2023) focused on socially disadvantaged people in broader terms. A participant needed to meet the following conditions: no reliable personal vehicle, travelling by local public transit, and being at least 18 years old. Whereas these studies focussed on a specific group and their perceived accessibility levels, Tanimoto and Hanibuchi (2021) evaluated the correlations between perceived accessibility and various personal factors, such as self-rated health, living in a central city, and household composition. Lastly, Liu et al. (2018) included perceived accessibility in their study to establish a relationship between the commuting trips of an individual and those of their parents.

Third, only two studies evaluated perceived accessibility with a main focus on geographical aspects. For instance, Wang et al. (2022b) performed a spatial analysis to evaluate whether elderly people are sufficiently included in the process of designing open spaces in urban cities. In addition, Pot et al. (2020) evaluated the perceived accessibility of rural-living individuals in Zeeland, the Netherlands.

Some studies include two or more aspects to evaluate perceived accessibility. These are Dharmowijoyo et al. (2020), Guzman et al. (2023), Naqavi et al. (2023), and Pot et al. (2023a). Dharmowijoyo et al. (2020) evaluated social and transport aspects and their influence on various perceived accessibility indicators. Guzman et al. (2023) also evaluated the effect of social and transport disadvantages, such as vehicle ownership, gender, income, household size, and occupation, on perceived accessibility. In contrast to Dharmowijoyo et al. (2020) and Guzman et al. (2023), Naqavi et al. (2023) and Pot et al. (2023a) evaluated social, transport, and geographical conditions on perceived accessibility.

While perceived accessibility is applied to a wide range of cases, a limited number of studies have explored heterogeneity in the perceived accessibility among individuals. Lättman et al. (2018); Lättman et al. (2020) evaluated differences in perceived accessibility between residential areas and travel modes. In addition, Azmoodeh et al. (2023) identified the accessibility levels for low-capability and high-capability respondents. Van der Vlugt et al. (2022) and Pot et al. (2023b) evaluated differences in perceived accessibility too. Whereas Van der Vlugt et al. (2022) revealed heterogeneity in walking accessibility, Pot et al. (2023b) evaluated the difference between rural and urban areas. These studies all use observed variables related to the social, transport, and geographical aspects encountered by disadvantaged individuals to reveal heterogeneity in the perceived accessibility by individuals. However, identifying groups by relating different perceived accessibility patterns that emerge from the data to social, transport, and geographical aspects is still lacking.

The purpose of this paper is to reveal perceived accessibility patterns from the data and to relate these patterns to social, transport, and geographical conditions often encountered by disadvantaged individuals in order to identify groups with different levels of perceived accessibility. To this end, we conduct a latent class analysis. To support the specification of the latent class model, a theoretical framework that links transport, social, and geographical disadvantages with perceived inaccessibility is proposed in Section 3.

3. Towards a framework for accessibility poverty

In this section, the accessibility poverty framework is outlined. This framework aims to provide working definitions of and relationships between social exclusion, accessibility poverty, transport poverty, and perceived inaccessibility. In addition, this framework aims to articulate the role of both objective and subjective accessibility measures in evaluating accessibility levels. By doing so, practitioners and scholars are informed on which concepts to focus on when addressing social exclusion and accessibility poverty. In addition, the groundwork for future attempts to integrate subjective with objective accessibility measures in quantitative analyses is provided. An example of an application of the accessibility poverty framework is provided in this paper, by revealing groups with different levels of perceived accessibility.

The accessibility poverty framework builds on the initial framework proposed by Lucas (2012) and relies on the analytical model used by Pot et al. (2020). While Lucas's framework underlines the role of transport in social exclusion, an objective evaluation of accessibility is used. Yet, objective accessibility measures are unable to capture the perceptions of individuals and differences between groups of individuals within geographical areas (Lättman et al., 2018). Consequently, the accessibility poverty framework adjusts the framework of Lucas (2012) by integrating objective with subjective accessibility measures as basis for the evaluation of accessibility levels. For this, we rely on the analytical model used by Pot et al. (2020) to study perceived inaccessibility based on transport, social, and geographical determinants. In addition, we articulate that the evaluation of accessibility poverty and social exclusion should involve setting a threshold based on the perceived accessibility levels experienced by the wider society, rather than solely relying on one's individual level of accessibility.

First, the framework illustrates what drives an individual's level of perceived accessibility. Here, we start off with the notion raised by Lucas (2012) that transport disadvantages (e.g. a lack of car ownership, poor public transport services) and social disadvantages (e.g. low income, older age) interact to cause transport poverty. An individual experiences transport poverty if *'he or she lacks access to adequate means of transport, limiting a person's potential mobility to reach or participate in activities'* (Jeekel and Martens, 2017, p. 2). It refers to a lack of resources (Martens, 2013), which arises from transport and social disadvantages. However, Pot et al. (2020) emphasise that geographical disadvantages may be encountered as well, in addition to transport and social disadvantages. This reasoning follows from the observation that accessibility is defined as *'the extent to which land-use and transport systems enable […] individuals to reach activities or destinations'* (Geurs and Van Wee, 2004, p. 128). Here, geographical disadvantages relate to the differences in the land-use system between areas. Often, rural-living individuals are perceived to be disadvantaged due to longer distances and lower densities of amenities and services in these areas (Pot et al., 2020). From this, we derive that longer distances and lower densities of amenities are indicators of geographical disadvantages.

The framework also articulates that these transport, social, and geographical aspects encountered by disadvantaged individuals interact to cause transport poverty and in turn perceived inaccessibility, as underlined by Pot et al. (2020). For instance, living in rural areas or a lack of car ownership does not necessarily result in transport poverty, but transport poverty may arise if a rural-living individual lacks the ownership of a car. In turn, perceived inaccessibility can be the result of transport poverty (Pot et al., 2020) and occurs if *'the perceived potential to participate in spatially dispersed opportunities'* (Pot et al., 2021, p.2) is low. In line with this, Lättman et al. (2016) defined perceived accessibility as *'how easy it is to live a satisfactory life with the help of the transport system'* (p. 258).

The subjective judgement of accessibility levels plays a determinant role in the accessibility poverty framework, in contrast to the framework by Lucas (2012) which applies an objective evaluation of accessibility, to make sure that the accessibility level perceived by an individual is fully reflected in the assessment (Martens and Bastiaanssen, 2019). Social exclusion remains a subjective experience, which is fueled by contextual factors that shape how individuals perceive their level of accessibility. Such contextual factors include social norms and practices, economic and political structures, and governance and decision-making (Lucas, 2012).

An illustration of the drivers behind transport poverty and perceived inaccessibility is shown in Fig. 1. Here, we underline that transport, social, and geographical disadvantages interact to cause transport poverty. Examples of disadvantages that may cause transport poverty are provided too. In turn, transport poverty may cause perceived inaccessibility. Contextual factors that shape how disadvantages and inaccessibility are illustrated as well. While these transport, social, geographical, and contextual aspects drive whether transport poverty and inaccessibility is experienced, accessibility poverty is rather driven by a lack of access to opportunities. Following Lucas (2012), accessibility poverty is defined as the *'lack of access to opportunities, such as employment, education, and*

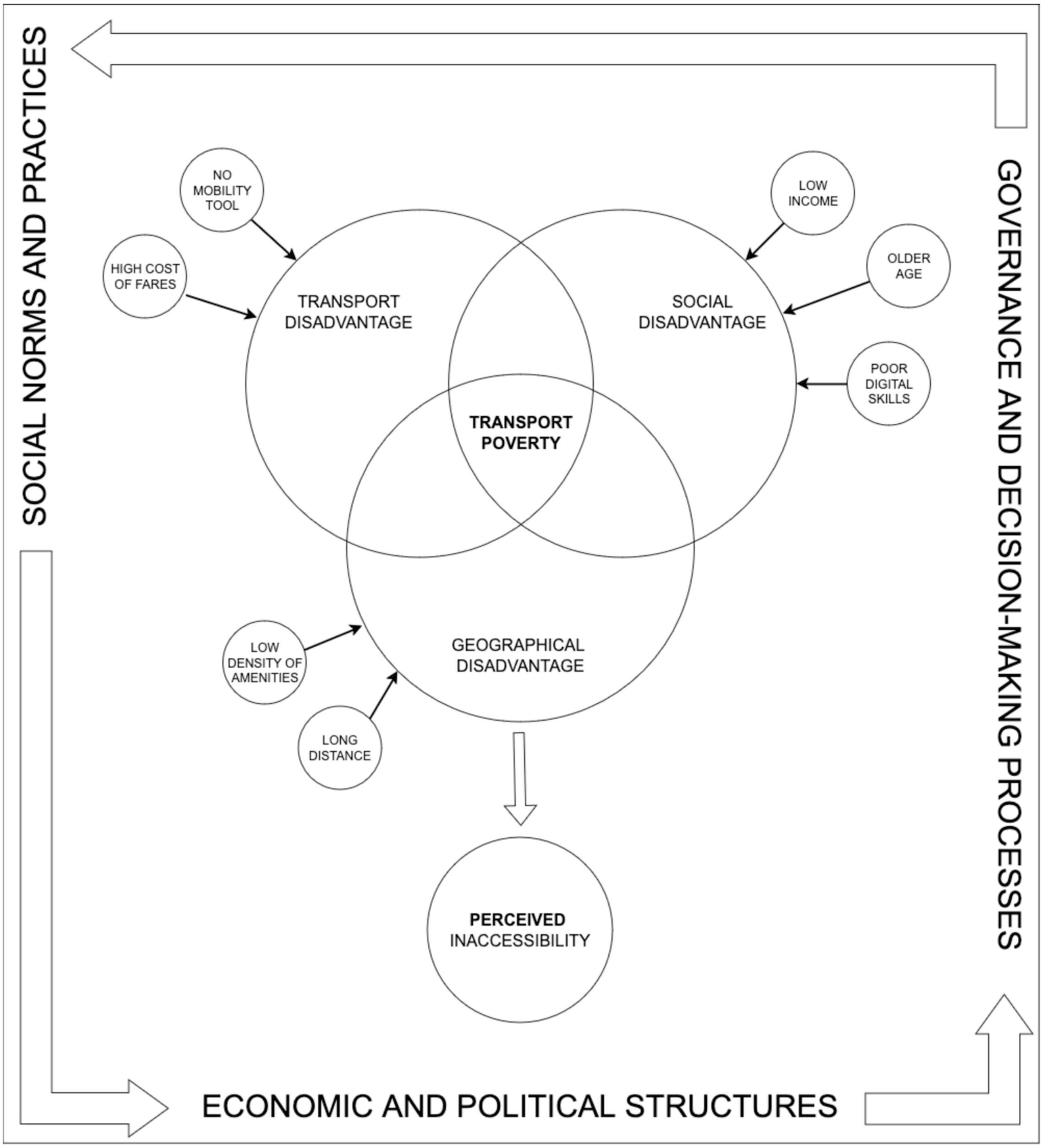

Fig. 1. Conceptualisation of the drivers behind transport poverty and perceived inaccessibility.

healthcare'. In other words, individuals who suffer from accessibility poverty have an insufficient level of accessibility to provide access to such opportunities. This highlights a subtle difference with transport poverty, concerned with the lack of resources available to individuals, which results in placing accessibility poverty outside individuals' frame as illustrated by Fig. 1.

Contrary to the framework proposed by Lucas (2012), the accessibility poverty framework underscores that the evaluation of accessibility poverty and social exclusion involves setting a threshold based on the perceived accessibility levels experienced by the wider society. For this, one may use the accessibility poverty line proposed by Martens and Bastiaanssen (2019). While Martens and Bastiaanssen (2019) emphasise that the accessibility poverty line does not ensure that all people above the line experience sufficient levels of accessibility whereas people below the line experience insufficient levels, this limitation is alleviated in the accessibility poverty framework since experiences are taken into account. Still, the threshold which represents a sufficient level of accessibility depends on normative judgement of the researcher.

In turn, accessibility poverty may lead to transport-related social exclusion if *'inadequate access to life-enhancing opportunities has a significant impact on a person's life'* (Jeekel and Martens, 2017, p. 3). However, it should be addressed that accessibility poverty does not necessarily imply (transport-related) social exclusion and vice versa. While an individual's level of accessibility might be low, this individual may still be socially included. Contrary, socially excluded individuals with low levels of participation do not necessarily experience low levels of accessibility too (Currie et al., 2010; Martens and Bastiaanssen, 2019).

In general, the accessibility poverty framework can be used to address accessibility poverty and perceived inaccessibility in a society. This paper illustrates the general points of the accessibility poverty framework by linking perceived accessibility patterns to transport, social, and geographical determinants of transport poverty using a latent class model. Section 4 shows how the accessibility poverty framework can be translated into a latent class model. Afterwards, Sections 5 and 6 provide the results of the latent class analysis and a discussion on the choice of variables and their implications on the model findings.

4. Methods

In this section, we discuss our methodology for revealing groups with different perceived accessibility patterns. To do so, a latent class model is developed in which these patterns are related to differences in transport, social, and geographical characteristics. For the measures used to construct the latent class model, we rely on the accessibility poverty framework proposed in Section 3.

4.1. Data

For the analysis, we use the Dutch National Travel Survey provided by Statistics Netherlands (n.d.). This questionnaire collects information about the daily travel patterns and preferences, of the Dutch population aged 6 years or older living in private households. A stratified sample is obtained, meaning that every segment of the population is represented in the dataset. First, municipalities are selected from a cluster of municipalities with an equal chance based on their number of residents. Second, simple random sampling, among the municipalities selected in the first step, is performed (Statistics Netherlands, n.d.). In total, 20,020 respondents were included in the analysis.

Table 1
Distribution of objective measures in the sample compared with population.

		Sample	Population[a]
Social dimension			
Gender (%)	Male	51	50
	Female	49	50
Age	Mean	45.9	42.4
Migration background (%)	Western	87	91
	Non-Western	13	9
Level of education (%)	Low	25	26
	Medium	32	38
	High	44	36
Employed (%)	No	52	46
	Yes	48	54
Spendable income (%)	Below €38.000	33	48
	Above €38.000	68	52
Geographical dimension			
Urbanity (%)	Rural	41	51
	Urban	59	50
Transport dimension			
Car ownership (%)	No	56	53
	Yes	44	47
PT student card (%)	No	94	97
	Yes	6	4
Driver's license (%)	No	27	35
	Yes	73	65

[a] Data retrieved from CBS Statistics Netherlands (http://statline.cbs.nl/Statweb/).

4.2. Measures

Here, information is provided on the measures used in the analysis. These measures are categorised as either objective or subjective measures.

4.2.1. Objective measures

Objective measures are chosen based on the individual frame of the accessibility poverty framework. The framework underlines that transport, social, and geographical disadvantages interact to cause transport poverty. In turn, transport poverty may result in perceived inaccessibility. For the latent class model, variables that represent such disadvantages are chosen. For the transport dimensions, car ownership as well as a driver's license and public transport student card are used. Socio-demographics gender, age, migration background, education level, income, employment status, and spendable income are included to measure the social dimension. Lastly, the level of urbanization is used to evaluate the geographical dimension. In Section 6, a discussion on the choice of these objective accessibility measures is provided.

Table 1 displays the sample distribution of objective measures compared to the distributions in the population. From comparing the sample with population distributions can be concluded that the sample is representative for gender. However, the mean age in the sample is 3.5 years higher than in the population. Also, migration background, educational level, spendable income, urbanity level, number of driver's licenses, and public transit student cards denote a higher percentage in the sample. Lastly, car ownership and employment are less represented in the sample compared with the Dutch population.

4.2.2. Subjective measures

The indicators used to measure perceived accessibility are shown in Table 2. Respondents are asked to rate accessibility levels of key activities or locations on a five-point Likert scale ranging from never accessible (1) to always accessible (5). Work, education, grocery stores, hospitals, general practitioners, train stations, local public transit, family and friends, and sports are included as activities or locations. The descriptive statistics of the perceived accessibility indicators show a high accessibility level perceived by the sample. This implies that accessibility is generally speaking perceived as high. In addition to a discussion on the choice of objective measures, Section 6 discusses the choice of the subjective measures too.

4.3. Analytical approach

To reveal heterogeneity in the perceived accessibility levels of individuals, a latent class analysis is conducted. Latent class analysis is often applied to identify different subgroups within the sample that share certain characteristics (Weller et al., 2020). For this study, the latent class model is able to reveal differences in perceived accessibility for subgroups which deviate in objective measures which depict transport, social, and geographical disadvantages. A latent class analysis is preferred over other clustering techniques, such as K-Means cluster analysis, since nominal and ordinal indicators can be used too (Kroesen, 2019). Since the perceived accessibility indicators are measured on an ordinal scale, latent class modelling is applied. Latent Gold was used to estimate the latent class models (Vermunt and Magidson, 2016).

In Fig. 2, the link between transport poverty and perceived inaccessibility as part of the accessibility poverty framework is translated to a latent class model. In the model, people their perceptions related to how well various destinations are accessible are used as indicators of the clusters. This will result in various transport poverty profiles i.e. groups that experience difficulties in reaching relevant destinations. The objective determinants known to be associated with transport, social, and geographical disadvantages are included as predictors of class membership.

The latent class analysis is conducted using a three-step approach. First, the measurement model, which includes indicators only, is constructed. Second, the most parsimonious model is obtained through estimating models with 1 through 10 latent classes. The goodness-of-fit of these models is given in Table 3. The model L^2 statistic indicates the amount of association among the variables that remains unexplained after estimating the model. The lower the value, the better the model fit. The P-value indicates whether the L^2 statistic is significant. A non-significant value indicates that the model is able to reproduce the observed patterns of scores on the indicators. Generally, among the models with a p-value greater than 0.05, the model with the smallest number of parameters is chosen.

Table 2
Descriptive statistics of the perceived accessibility indicators.

Indicator	Mean	Std. dev.
How often reachable when needed?		
Work	4.9	0.6
Education	4.8	0.7
Grocery store	4.9	0.4
Hospital	4.8	0.6
General practitioner	4.9	0.5
Train station	4.8	0.7
Local public transit	4.8	0.7
Family and friends	4.8	0.6
Sport	4.8	0.7

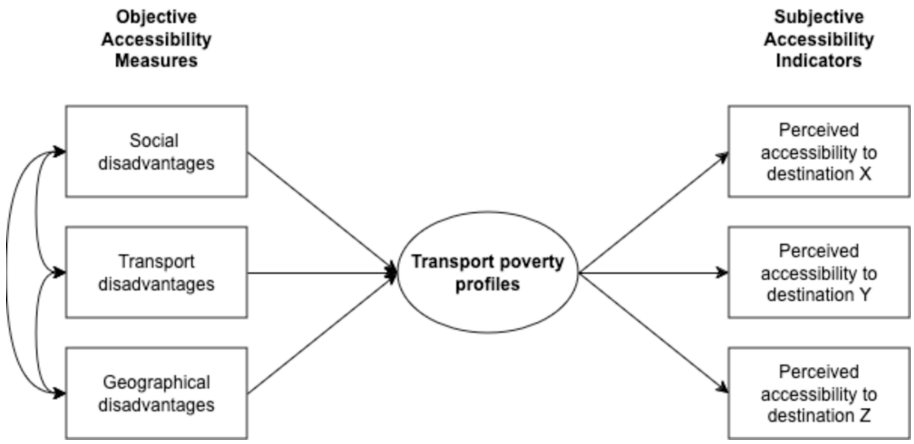

Fig. 2. Formalisation of latent class model using the Accessibility Poverty Framework.

Table 3
Model fit of the latent class models.

No. of classes	Npar	LL	P-value
1	36	−80,115.76	0.00
2	46	−57,582.91	0.00
3	56	−53,449.27	0.00
4	66	−52,644.85	0.00
5	76	−52,051.68	0.00
6	86	−51,495.78	0.40
7	96	−51,129.41	1.00
8	106	−50,893.13	1.00
9	116	−50,668.11	1.00
10	126	−50,488.73	1.00

Npar = number of model parameters.
LL = final log-likelihood.

Hence, the 6-class model is considered as optimal.

Here, we would like to address the evaluation of the latent class model. For this, we rely on Weller et al. (2020). First, the choice of indicators should be evaluated. As Weller et al. (2020) emphasises, there is no consensual view on how many indicators to include in the model. The latent class model includes 7 perceived accessibility indicators, which falls within the range of 4 to 20 indicators often used (Weller et al., 2020). In addition, the Cronbach's alpha underlines a high internal consistency between the perceived accessibility indicators used in this paper (α equals 0.93, with a small variation if one of the items is deleted). Second, the optimal number of classes should preferably be derived through the three-step approach which involves identifying the measurement model and then adding covariates (Weller et al., 2020). Here, the measurement model includes indicators only, for which the most parsimonious model is obtained through estimating the measurement model for 1 to 10 classes. Following this approach, the measurement model with six classes can be considered the most parsimonious. Third, the operationalisation of covariates should be addressed too. While adding covariates allows researchers to evaluate whether classes differ in observed characteristics, a different operationalisation of these observed characteristics may lead to different model findings. Nonetheless, we applied the approach proposed by Weller et al. (2020) to collapse the variables' initial levels into two or three levels to make it easier to interpret the class allocation. Besides, the latent class model denotes a classification error rate of 0.0374, implying that the classification of individuals is adequate.

5. Results

Table 4 presents the class sizes and profiles of the six classes. The sample distribution is included to ease the interpretation. For each covariate, the Wald statistic is included too. This statistic indicates whether the covariates significantly influence segment membership (Vermunt and Magidson, 2016). Fig. 3 shows the variance in perceived accessibility levels across clusters. Since age is an important determinant of class allocation (following from the size of the Wald statistic), class identification is strongly based on the average age within the classes.

The first class represent subjects that perceive a high accessibility level on all indicators. The majority of the subjects are allocated to this class (78.1 % of the sample). These early middle-aged adults, with an average age of 41 years, are highly educated and employed more often, compared to the other classes. Also, a high share of individuals with a spendable income greater than €38.000 is allocated to this class.

Table 4
Latent class model results.

	1	2	3	4	5	6	Sample
Size (N = 20020)	78.1 %	10.8 %	4.7 %	3.4 %	2.3 %	0.7 %	
Indicators (5-point Likert scale)							
Work	5.0	4.8	4.4	5.0	2.5	2.2	4.9
Education	5.0	4.7	4.1	4.8	2.0	1.2	4.8
Grocery store	5.0	5.0	4.5	5.0	3.4	5.0	4.9
Hospital	5.0	4.7	3.8	4.8	2.5	5.0	4.8
General practitioner	5.0	4.9	4.1	5.0	2.6	5.0	4.9
Train	5.0	4.9	3.8	3.8	2.0	2.8	4.8
Local public transit	5.0	4.9	3.9	3.7	2.1	2.8	4.8
Family	5.0	4.4	3.9	4.8	3.0	4.6	4.8
Sport	5.0	4.7	3.8	4.8	2.2	3.2	4.8
Covariates (%)							
Gender (Wald = 33.9, p-value = 0.0)							
Female	45.2	56.3	52.7	48.3	45.1	45.3	53.1
Male	54.8	43.7	47.3	51.7	54.9	54.7	49.2
Age (Wald = 463.7, p-value = 0.0)							
Average age in years	41.4	27.0	32.2	35.4	52.5	69.2	45.9
Migration background (Wald = 416.8, p-value = 0.0)							
Western	88.3	80.6	60.0	84.8	60.2	92.9	86.0
Non-Western	11.7	19.4	39.9	15.2	39.8	7.1	13.0
Education (Wald = 148.6, p-value = 0.0)							
Low	12.6	20.5	24.0	25.4	50.2	57.6	24.5
Middle	32.9	40.1	39.4	41.8	27.9	24.7	31.6
High	54.5	39.3	36.6	32.8	21.9	17.8	43.9
Employment (Wald = 91.4, p-value = 0.0)							
Not employed	23.7	55.0	44.9	33.9	69.2	82.4	48.1
Employed	76.3	45.0	55.1	66.1	30.9	17.6	51.9
Spendable income (Wald = 152.4, p-value = 0.0)							
Below €38.000	20.6	33.5	37.0	16.3	61.5	65.9	32.5
Above €38.000	79.5	66.5	63.0	83.7	38.5	34.1	67.5
Urbanity (Wald = 122.0, p-value = 0.0)							
Rural	40.6	27.7	33.3	66.5	36.6	51.5	41.2
Urban	59.4	72.3	66.7	33.5	63.4	48.5	58.8
Car ownership (Wald = 119.8, p-value = 0.0)							
No car	48.4	87.6	74.0	56.0	62.8	46.8	54.4
Car	51.6	12.4	26.0	44.0	37.3	53.2	43.6
PT student card (Wald = 74.2, p-value = 0.0)							
No PT student card	91.2	61.9	74.5	81.4	94.6	100.0	54.4
PT student card	8.8	38.1	25.5	18.6	5.4	0.0	6.0
Driver's license (Wald = 224.3, p-value = 0.0)							
No driver's license	11.3	43.4	41.9	20.9	42.6	19.9	27.0
Driver's license	88.7	56.6	58.1	79.1	57.4	80.1	73.0

The second class (10.8 % of the sample) includes a relatively small number of subjects, while it is the second largest class. These subjects perceive work, education, hospital, family, and sports as having low accessibility when compared to the sample average. However, these perceived accessibility levels do not deviate from the sample average much. Other locations are perceived as highly accessible. These travellers do not own a car, however, are in possession of a public transport student card. With an average age of 27 years and a relatively large number of subjects with a middle completed educational level, this class mainly represents students.

The third class (4.7 % of the sample) represents starters who perceive accessibility as lower compared to the sample. Compared to the second class, the third class also represents subjects with a middle education, yet the employment rate is higher in the third class. Also, the number of subjects with a public transport student card is lower and the subjects are on average 5 years older in the third class. However, spendable income is interpreted as moderate compared to other classes. Also, a large share of individuals within this class are living in urban areas. Hence, this class is identified as middle-income, urban-living starters.

The fourth class (3.4 % of the sample) denotes higher perceived levels of accessibility compared to the third class, while the accessibility level of local and nationwide public transport is perceived as lower. However, subjects live in rural areas and possess a car and driver's license more often. A relationship between the quality and quantity of public transport, level of urbanisation, and car ownership arises. Nonetheless, subjects are employed more frequently and have a higher spendable income compared to subjects allocated to the third class. Consequently, accessibility levels are perceived as higher due to these characteristics. As such, this class is identified as high-income, rural-living starters.

The fifth class (2.3 % of the sample) suffers from overall low perceived accessibility levels compared to the other classes. Subjects allocated to this class are lower educated and unemployed more often. Also, this class denotes one of the largest shares of individuals with a non-Western background. Besides, this class has a high share of individuals with a spendable income lower than €38.000. Nonetheless, the age of this class is also higher compared to the sample, with an average of 53 years. As such, the fifth class is identified as late middle-aged individuals.

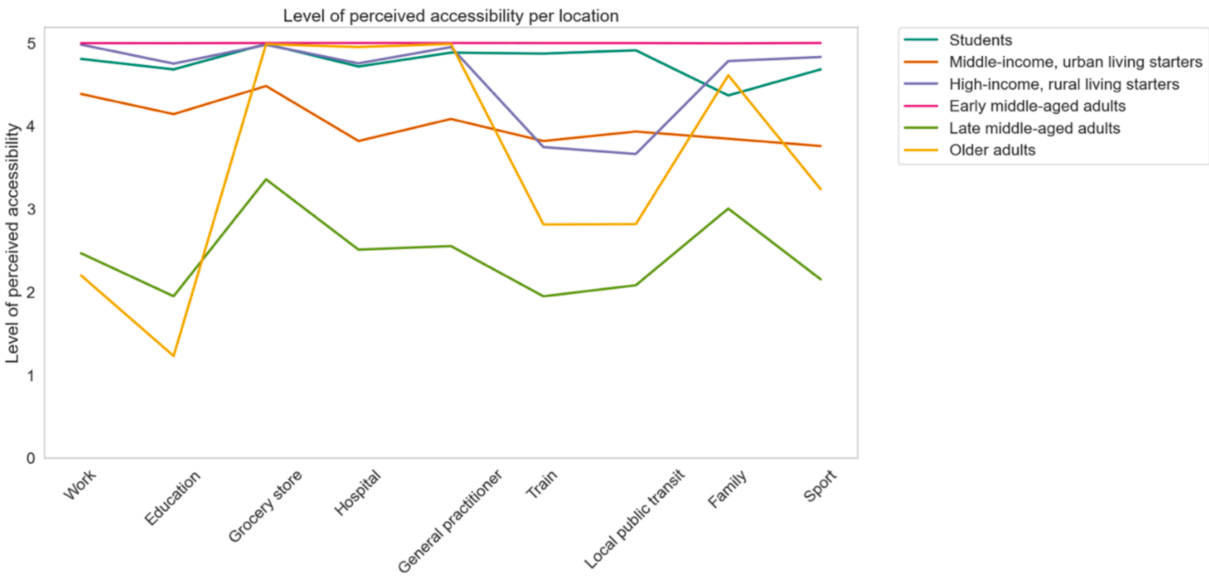

Fig. 3. Perceived accessibility levels across classes.

The last class (0.7 % of the sample) suffers from low accessibility levels for half of the locations. Grocery stores, hospitals, general practitioners, and families are highly accessible, whereas work, education, train, local public transit, and sports are perceived as low accessible. An interesting finding is that the accessibility of locations important to the elderly seems to score high, whereas the accessibility of less important locations scores low. Aligned with characteristics of individuals allocated to the fifth class, subjects are lower educated and unemployed more often compared to the sample. The spendable income is lower than €38.000 for this class. Age seems to be an important determinant for allocation to this class, with an average age of 69 years. Consequently, this class is identified as older adults.

6. Discussion

Several studies revealed differences in perceived accessibility among individuals, yet these studies often define ex-ante observed characteristics for which differences in perceived accessibility levels are studied. For instance, Lättman et al. (2018) compared the levels of perceived accessibility for travel modes and residential areas of Malmö. While perceived accessibility did not vary extensively across residential areas, bike users perceive a different level of accessibility compared to users of other travel modes. Whereas Lättman et al. (2018) focused on heterogeneity in the level of accessibility for different residential areas and travel modes, Lättman et al. (2020) revealed that car users have a higher level of perceived accessibility than users of alternative modes. In accordance, Pot et al. (2023b) underlined that a lack of car ownership is a major contributor to inadequate access for individuals living in rural areas. However, perceived accessibility did not differ significantly between urban and rural areas. Hence, the lack of car and bike ownership as transport disadvantages seem to contribute to perceived inaccessibility extensively. While Van der Vlugt et al. (2022) studied the perceived accessibility of walking, they concluded that these perceptions are not significantly affected by individual characteristics such as gender, age, income, and education. Contrary, Azmoodeh et al. (2023) conclude that social disadvantages play a relevant role in the perceived capabilities of an individual, by identifying low- and high-capability groups based on income, age, and education. A higher level of income has a significant association with the high-capability group, underlining that an increase in financial resources results in greater access to opportunities (Azmoodeh et al., 2023). In addition, older age is associated with lower perceived capabilities (Azmoodeh et al., 2023). In general, consensus on which disadvantages drive differences in perceived accessibility is lacking among these studies.

While earlier studies used ex-ante groups to identify differences in perceived accessibility, this paper revealed groups with different perceived accessibility levels by ex-post linking differences in perceived accessibility patterns with transport, social, and geographical characteristics. By doing so, model findings highlight that the majority of respondents perceive excellent levels of accessibility, whereas a minority of respondents perceive lower levels of accessibility to some extent. For those groups that perceive inaccessibility, age, migration background, and possessing a driver's license seem to be the main contributors. The observation that older age is associated with perceived inaccessibility is in line with the observation of Azmoodeh et al. (2023), however, the role of migration background and possessing a driver's license on differences in perceived accessibility often remains unexplored in previous studies. Yet, the latent class model highlights their relevance in identifying different groups. In addition, car ownership and the level of urbanization contribute to differences in perceived accessibility, yet this role is less prominent than earlier concluded by Lättman et al. (2020) and Pot et al. (2023b). Overall, the latent class analysis showed that social rather than transport and geographical aspects determine perceived inaccessibility to a large extent.

7. Conclusion

This paper aimed to address accessibility poverty by identifying groups with different levels of perceived accessibility. To achieve this aim, we developed a latent class model that relates perceived accessibility patterns to social, transport, and geographical aspects encountered by disadvantaged individuals. Examples of such aspects are, but not limited to, age, income, and car ownership. To support the model specification, a theoretical framework that links transport, social, and geographical disadvantages with perceived inaccessibility and accessibility poverty was developed. The research findings lend support to tailored policies aimed at reducing accessibility poverty and social exclusion for specific segments of the population.

The first finding is that only small segments of society experience lower perceived accessibility to some extent compared to the majority of citizens. The latent class analysis highlighted that around 89 % of the respondents experience excellent accessibility, whereas around 11 % of the respondents experience lower accessibility to some extent. More specifically, two classes suffer from the lowest levels of perceived accessibility extensively. The first class represents late middle-aged individuals (2.3 % of the sample), whereas the second class represents older adults (0.7 % of the sample). While these classes share some characteristics, such as a low level of education, low employment rate, and low spendable income, the classes distinguish themselves with respect to age and migration background. The Wald statistics highlight that these covariates are most influential in class allocation.

The second finding relates to the effect of covariates on class allocation. The latent class model highlights the significant role of age and migration background as well as possessing a driver's licence for class allocation. In addition, car ownership and the level of urbanization contribute to differences in perceived accessibility, yet this role is less prominent than earlier concluded by Lättman et al. (2020) and Pot et al. (2023b). For instance, individuals living in rural areas do not necessarily perceive accessibility to be low. This heavily depends on whether other disadvantages are encountered too. Take for instance the middle-income, urban living starters and high-income, rural living starters. Overall, the latent class analysis showed that middle-income, urban living starters perceive lower accessibility levels compared to high-income, rural living starters. In contrast to the findings of earlier studies, rural-living individuals do not necessarily perceive inaccessibility in comparison to urban-living individuals. The role of other disadvantages, such as a lower spendable income, should not be underestimated. These findings support the notion that social, transport, and geographical disadvantages interact to cause transport poverty, which in turn results in perceived inaccessibility.

This study offers several implications for policy and practice. First, research findings highlight that a majority of the respondents perceive excellent levels of accessibility, whereas a minority of the respondents (around 11 %) experiences lower levels of accessibility to some extent. Hence, accessibility poverty and social exclusion may lurk for these smaller segments of society. Furthermore, social rather than transport and spatial aspects determine perceived inaccessibility. As a consequence, transport policies designed to lower accessibility disparities should focus on the social aspects of individuals, such as age or income. To do so, policymakers are recommended to formulate strategies which mitigate or prevent perceived inaccessibility for specific social groups. For instance, Liu et al. (2021) studied the effect of smartphone-based services on perceived accessibility and concluded that policymakers should ensure that disadvantaged individuals are not further disadvantaged through policy interventions. An example is to design user-friendly and affordable smartphone designs for older adults (Liu et al., 2021). In addition, as highlighted by Durand et al. (2022), trainings and workshops among these older adults might increase digital skills as well. Contrary, Pot et al. (2023a) concluded that perceived accessibility is mainly moderated through socio-demographics characteristics and mobility tools. From the analysis follows that the ownership of an e-bike in the households relates to higher levels of perceived accessibility (Pot et al., 2023a). Becoming an e-bike owner, through policy incentives, might help certain social groups with increasing their perceived accessibility.

While our research proposed an integrated approach to study heterogeneity in perceived accessibility by linking subjective with objective measures, this study can benefit from further research. Contextual factors as well as adaptive preferences could play a role in perceived inaccessibility and accessibility poverty, yet these components are not elaborated on in this study. Van Wee (2016) underlines that research on perceived accessibility is often conducted based on one case or area, which differs with respect to culture, social norms, and practices. Hence, the importance of context stays unexplored. In addition, Pot et al. (2023a) highlight that qualitative studies have not pointed towards lowering accessibility standards for individuals experiencing social exclusion or transport poverty, while adaptive preference is often neglected in quantitative research thus far. By assessing perceived accessibility using panel data, adaptive preferences and external influences can be studied in future research.

In addition, we want to emphasize three recommendations that follow from the latent class analysis. First, we want to urge all national travel surveys to use the Perceived Accessibility Scale (or other validated scales) to ensure consistency in the measurement of perceived inaccessibility across national studies. Second, future attempts to integrate subjective with objective accessibility measures are recommended to carefully consider the measures used in the analysis. The choice of objective accessibility measures is not self evident. Whereas the level of urbanization may serve as a proxy for geographical conditions encountered by disadvantaged individuals, lower densities of amenities and longer distances between amenities were originally proposed as geographical disadvantages by Pot et al. (2020). Consequently, we want to stress that future attempts to integrate subjective with objective accessibility measures should be more careful in considering which objective accessibility measures, and in particular geographical disadvantages, are chosen. For this, the Accessibility Poverty Framework could be used to rely on. Also, we want to make policymakers aware that the latent class model does not ensure proper class assignment. As stressed by Weller et al. (2020), a relevant limitation is that individuals are assigned a probability of belonging to a class, which implies that individuals may be allocated to two or more classes. In addition, some individuals may not be represented by any of the classes. Consequently, proposing policies to reduce perceived inaccessibility for a certain class may not directly result in higher accessibility levels in practice. Lastly, names are assigned to the different classes to facilitate an easier interpretation of these classes. However, Weller et al. (2020) addresses that these names may engage in 'naming fallacy', implying that the name does not accurately represent the class membership. From our point of view, this naming fallacy is minimized by using the main determinant of class membership, namely age. Nonetheless, we want to underline that this does not imply that all classes are only deviating with regard to age, also other covariates determine the class membership.

In conclusion, the latent class analysis revealed groups with different perceived accessibility by ex-post linking perceived accessibility patterns with objective accessibility measures representing possible transport, social, and geographical disadvantages. The analysis highlighted only small segments of the population suffer from perceived inaccessibility. For these segments, accessibility poverty and social exclusion may lurk. In addition, social rather than transport or spatial conditions encountered by individuals determine perceived inaccessibility. These findings can inform policymakers and practitioners on which segments of the population to focus on when formulating policy on accessibility poverty and social exclusion.

CRediT authorship contribution statement

Milan L. Moleman: Writing – original draft, Visualization, Methodology, Formal analysis, Conceptualization. **Maarten Kroesen:** Writing – review & editing, Writing - original draft, Methodology, Supervision.

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