

Improving access to public transport by mapping passengers to the co-domain of mobility barriers

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ABSTRACT

This study proposes a framework that maps passengers to the co-domain of mobility barriers and to use only the latter when developing solutions for improving access to public transport. By applying Item Response Theory to a convenience sample of people disproportionately affected by disabilities, we estimate the latent risk of failing to access public transport for each barrier type. The analysis shows that personal characteristics and barriers are systematically related to varying extents, even within groups of individuals with the same impairment. Therefore, we suggest moving beyond average associations and instead constructing a privacy-respectful, actionable, and personalised barrier-data information system that maps passengers to the barrier co-domain. The paper details practical implementation steps and discusses benefits and limitations.

1. Introduction

Improving access to public transport can help deliver social equity and inclusion of vulnerable groups (Intergovernmental Panel on Climate Change, 2023). The European Union has a legislative framework to ensure accessibility for persons with disabilities and persons with reduced mobility across transportation modes and infrastructure. It takes the form of “Technical Specifications for Interoperability” for “Persons with Disabilities and Reduced Mobility” and various other directives and regulations (European Union Agency for Railways, 2025). The United Nations Sustainable Development Goals and the 2030 Agenda for Sustainable Development also emphasise the importance of providing accessible and sustainable transportation systems for all citizens, including the development of public transport; and in the United States the Americans with Disabilities Act Standards for Transportation Facilities issued by Department of Transport provides standards for facilities (U.S. Access Board, 2025) used by state and local governments providing public transport services. Nevertheless, access to public transport remains limited or even impossible for many individuals, be it because of physical disabilities (e.g. Carlsson, 2004), cognitive impairments (Risser et al., 2015), or other characteristics like being a woman (e.g. Bezyak et al., 2020). As a result, individuals depend on others to participate in social activities and society at large (Neven & Ectors, 2023).

This study makes three contributions. First, it uses an Item Response Theory model to measure latent risk of failing to access public transport, which has several advantages. Second, using a convenience

sample of individuals disproportionately affected by impairments, it quantifies systematic relationships between 10 passenger characteristics and 34 mobility barriers and their within and between variation. This goes beyond the usual approach of research focusing only on one or few specific groups or types of impairments. The results highlight that passengers with the same characteristic can be affected differently by the same mobility barrier; and a given barrier can be relevant across passengers with different characteristics. Grouping passengers by characteristics may be therefore not as effective when trying to improve access to public transport. This leads to the third and main contribution. Section 4 introduces the notion of mapping passengers to the co-domain of mobility barriers to improve access to public transport. Benefits and limitations of this approach are explained and suggestions for practical implementation are made.

2. Defining mobility barriers

Before discussing the literature, we explain the term ‘mobility barrier’ as it is understood in this study. Difficulties with access to public transport can be viewed as arising from the interaction between an individual’s impairments or other characteristics and the mobility barriers they encounter in their environment. Conceptually, this notion aligns with the social model of disability (for an overview see Oliver, 2013). It posits that society disables individuals through exclusionary practices and attitudes, rather than impairments themselves being the

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primary source of disadvantage. Accordingly, the International Classification of Functioning, Disability and Health of the World Health Organisation describes disability as the interaction between features of the individual (functioning) and the overall context in which the individual lives (contextual factors) (World Health Organisation, 2001). The social model of disability identifies attitudinal, institutional and environmental barriers. Some studies mention barriers as they pertain to the social environment, for example, stress that older adults experience due to social expectations of being as quick as a young healthy person (Ravensbergen et al., 2021). Other studies use the term barrier to describe conditions like autism spectrum disorder and attention deficit/hyperactivity disorder (e.g. see Bolic Baric et al., 2024). This is different to our definition which sees barriers as *external* to the individual and therefore as features of their environment. This includes infrastructure, vehicles and the digital environment. Thus, a ‘mobility barrier’ is any physical, digital, or vehicle-related features that can prevent individuals from accessing public transport services. Examples are stairs, missing audio assistance, low contrast displays, noise, missing seating, or crowding.

3. Literature review

Literature on barriers to accessing public transport is extensive. As a result, several systematic reviews have been conducted in recent years. Risser et al. (2015) focus on individuals with cognitive impairments. They analyse 34 papers and identify needs as they arise along the travel chain when using public transport. A systematic review of 26 studies by Unsworth et al. (2021) focuses on users with mobility impairments, and Bolic Baric et al. (2024) review 11 studies that focus on groups with autism spectrum disorder and attention deficit hyperactivity disorder. These reviews tend to discuss barriers relevant to groups of individuals with the same or related impairments. By focusing on specific groups, they help understand how a given group's access is currently being hindered and how to improve it. Not all studies use a quantitative approach, but this is akin to identifying the relevant mobility barriers of an average member of a group whose members share a given characteristic.

It is important to understand between-group variation of mobility barriers. If the same mobility barrier is relevant to different groups, alleviating it is an efficient way of improving access across different groups. On the other hand, if groups are affected by separate sets of mobility barriers, decisions have to be made about how to fairly allocate limited resources for alleviating mobility barriers. Only the scoping review by Mwaka et al. (2024) allows making inferences about this type of between-group variation by focusing on different groups including those with physical, visual, auditory, intellectual, and mental disabilities, or speech conditions. Based on 34 studies the authors investigate mobility barriers and facilitators to public transport. They collate mobility barriers at different stages of the journey, which include getting to and from public transport stops or stations, waiting at stops or stations, and boarding, alighting and travelling in public transport vehicles. While the authors do not explicitly discuss the issue of commonalities or differences of mobility barriers across the different groups, their results show some mobility barriers that are common across multiple groups. Examples are the presence of stairs in railway stations at stops and stations; the presence of steps at the vehicle entrance when boarding and getting of the public transport; the lack of seats or inadequate seats when waiting at stops or stations; and lack of space; or less space for accessible seating within the public transport vehicle.

Next, within-group variation of mobility barriers arises when individuals who have the same characteristic are differently affected by the same barrier. Some evidence of this we find in Engel et al. (2020) who look at requirements for maps and indoor aids of two groups — people with blindness and people with low vision. They find evidence of within-group variation of requirements and conclude that aids should be individually adaptable to different orientation strategies and not be

divided according to the classic groups of people with blindness and low vision.

Thus, the literature provides some evidence of variation of mobility barriers both within and between different groups of public transport users. However, this within and between group variation is not explicitly discussed. This is partly explained by studies often focusing on groups of individuals with the same characteristic or using qualitative research methods, which cannot quantify variation. However, this variation is relevant when it comes to developing data driven solutions to improving access to public transport. It means that having information about someone's characteristics may not suffice to predict which barriers are relevant to them.

4. Theoretical framework

Different to previous studies that quantify ability to access or the impacts of barriers for different groups, this study draws on Item Response Theory (IRT). It is used to estimate individual risk scores and uncover which mobility barriers are linked to which personal characteristics. IRT originates in education research (see Lord, 1980; Sedransk, 2018). It is used to measure ability as a latent and continuous construct from individual responses to different sets of survey items that vary in difficulty. In contrast to previous approaches where Likert score values are treated as direct measurements without requiring a theoretical foundation, IRT explicitly recognises the hypothesis of a latent trait that exists and that is both quantifiable and measurable, as operationalised by a survey instrument.

Other applications of IRT in transport research include Cheng (2011) who evaluate bicycle-transit users' perceptions of the latent construct 'intermodal inconvenience'. They identify factors that lead to differences in perceived inconvenience such as sex, riding frequency, trip purpose, and environmental awareness. Cheng and Chen (2015) measure the latent constructs of accessibility, mobility, and seamless connectivity for a public transportation service chain in two large cities in Taiwan. They find that perceived accessibility, mobility, and seamless connectivity differ based on travellers' age, frequency of weekly sports activities, and environmental awareness.

Because IRT distinguishes between characteristics of individuals (their ability), and of items (their difficulty), it is particularly suited to quantifying accessibility. Depending on which data are available, it can be used to learn who is particularly vulnerable due to lack of “ability”, which barriers are particularly difficult to overcome, or both. Accordingly, this study postulates that each passenger has a latent trait, which represents their “dis-ability” or risk of failing to access public transport when encountering barriers. The latent trait cannot be directly observed. It varies systematically with personal characteristics, and it can be measured from survey responses to different items where each item refers to a different barrier. IRT assumes that the latent trait can only be learned, if survey items include all relevant items. To this effect, a focus group with experts on diversity and inclusion was conducted on this topic (see Section 5.1). IRT does not invoke any assumptions about the distribution of levels of the latent trait in a population. This aligns well with the fact that due to a lack of data, little is known about how the risk of failing to access public transport is distributed among passengers some of which are affected by multiple impairments.

The notion of mapping passengers to the co-domain of mobility barriers is explained in Fig. 1. Personal characteristics are responsible for increasing an individual's risk of failing to access public transport at a given point in time. Personal characteristics are observable and could be learned from survey data, for example. They give information about how well a passenger may be able to overcome a given barrier. However, people often prefer keeping information about their personal characteristics, such as impairments or disabilities, private. Instead, latent risk of failing to access public transport at a given point in time can be assessed from the barriers that a passenger does or does not

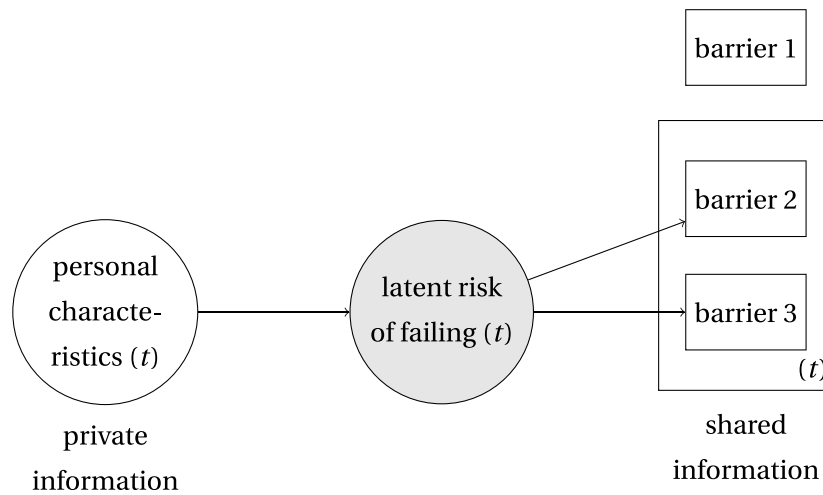


Fig. 1. Mapping a passenger to mobility barriers via the latent trait. White nodes are observable and grey nodes are unobservable. The passenger's personal characteristics at time t affect their latent risk of failing to access public transport. This information is private. Instead, the passenger indicates which barriers are relevant to them, namely barriers 2 and 3.

overcome. By share which barriers hinder their access, passengers can communicate their requirements to transport providers. The barriers and their attributes may vary over time as characteristics or circumstances change. For example, a person's abilities may change or stations may be deserted at night. Information about barriers is arguably more helpful to the service provider than knowing the causes (impairments), whilst also being less revealing for the passenger. Other advantages and limitations of this approach are discussed in the light of the empirical findings in Section 7.

5. Methods

This section presents results from a survey of public transport users in Germany. Risk of failing to access public transport is estimated as a function of characteristics and impairments. The strength of associations between characteristics and mobility barriers are measured and their within and between group variations are quantified.

5.1. Expert discussion

To ensure that all potentially relevant mobility barriers are identified, a workshop with experts on diversity and inclusion was conducted. The ten participants included researchers, representatives from public transport companies and the city of Leipzig, and a diversity commissary. The workshop lasted two hours and was conducted online in August 2022. Initially, potential mobility barriers in the context of infrastructures, transportation means, and apps were collected and discussed. Then, participants discussed which personal characteristics or conditions might cause individuals to be affected by these mobility barriers and to what extent. Next, desiderata for the design of transport services and infrastructure were derived. In this context, participants expressed concerns about passengers having to provide health related information to public transport service providers. Finally, participants were asked to prioritise and weigh mobility barriers and their impacts on different groups of passengers. The final result is a list of mobility barriers grouped into six different domains, which is reported in Table 1 and forms the basis for the survey questionnaire.

5.2. Survey and data

The data were collected between November 2022 and January 2023 and are available on the platform mobilithetk ([German Ministry of Transport, 2025](#)). The survey was conducted online so as to take advantage of mailing lists provided by the organisations mentioned above. This way a large number of individuals in the realm of disability and inclusion could be reached. The survey was designed such that it could be read with the aid of text-to-speech readers and additional prompts were provided to facilitate access for visually impaired and potentially also for cognitively impaired individuals. Respondents were recruited by the research team and associated project partners. The link to the online-survey was distributed through various channels including posts on social media on private accounts and the research institution's accounts as well as those of the project partners. Additionally, 32 organisations and interest groups from the fields of mobility, public transportation, inclusion, disability, and diversity were specifically contacted via email and asked to distribute the survey within their organisations and networks. This strategy was used to maximise information in the data on associations between passengers' characteristics and mobility barriers, so that they can be estimated. But, this form of sampling results in individuals with impairments or other characteristics being overrepresented compared to the general population. The implications of this are discussed.

The survey questionnaire consisted of four sets of questions. The first set asked respondents about their transport behaviour. The second set asked respondents to state how likely they were to cancel or reject a journey when using public transport, if it included a given barrier. The survey question was: "When using public transport, how likely are you to not make or cancel a journey, if it involves [barrier]?". Responses are on a 5-point Likert-Scale with categories "highly likely" (5), "likely" (4), "neither likely, nor unlikely" (3), "unlikely" (2), and "highly unlikely" (1). Third, respondents were asked to indicate if they had any characteristics such as learning difficulties, difficulty walking, autism, difficulty hearing, difficulty seeing, poor sense of direction, being very tall, being very small, being overweight. We also asked for difficulties understanding the German language, but there were too few responses to obtain valid estimates. No questions were asked about any medical conditions. The last set of questions asked for socio-demographic information.

Table 1

List of potential mobility barriers to accessing public transport (survey items) based on results from the workshop.

Domain	Mobility barrier
Changeover/travel time	Short changeover and waiting times Long changeover and waiting times Travel requires multiple changeovers No other transport modes available (bike or carsharing, taxi)
Travel comfort	No seating in vehicles No seating at stops No holds and handlebars in trains and busses No toilets in vehicles or at stations No ticket office
Communication and orientation	To understand pricing careful study is required Stops are difficult to find No information about options for onward travel
Experience, quality of stay and surroundings	Unknown or new types of transport modes (e.g. e-scooter, carsharing) Crowded pathways, stops and vehicles Air at pathways and stops is polluted Noisy pathways, stops and vehicles Dirty vehicles and stops No protection from sun at stops and on pathways No protection from rain at stops and on pathways
Physical and digital accessibility	Stairs Escalators Narrow pathways No accessible toilets Stations and stops not accessible No help de-/boarding No tactile orientation and guidance system No voice outputs e.g. for departures or delays Online-booking only Travel advice requires using a mobile phone
Safety	Car traffic and pedestrians are not clearly separated No pedestrian crossings Poorly lit pathways and stops Persons who are perceived to be threatening in vehicles and at stations No or hardly any people on pathways, stops and in vehicles

In total 1019 persons responded to the survey. After removing incomplete responses and one person who indicated that they are both very tall and very small, the final sample size is 814, with 56 percent women or diverse and 43 percent men. Table 2 shows that very young and very old people are underrepresented, as are people with higher household incomes. Most respondents reside in urban areas with more than 500,000 inhabitants. A possible reason for this is that the organisations that were used to reach out to respondents are located and have most of their members in larger cities. A positive implication of this is that because public transport is more available in larger cities, these respondents are likely to have extensive experience using public transport whilst being impaired.

In the sample, 349 respondents report having at least one of the impairments or characteristics included in the survey. Table 3 shows the distribution of combinations of characteristics in the sample. The diagonal axis (in grey) depicts the total number of respondents who report to have a given characteristic. Each column shows for a given characteristic the number of combinations with other characteristics. Most common characteristics are being female or diverse, having difficulties seeing, having a poor sense of direction, and having difficulties walking. Some combinations of characteristics are also relatively common. For example, out of the 117 people who have difficulties seeing, 32 also have a poor sense of direction, 32 also have difficulties walking and 29 also have difficulties hearing. Learning difficulties and a poor sense of direction tend to have the most co-occurrences with other characteristics.

Table 2

Relative frequencies of categories for age, income, household size and city size (in %), N = 816.

Age (years)		Household income (Euros/month)	
<25	5.6	>1.500	15.6
25–45	37.3	1.500–3.999	49.8
46–65	41.1	4.000–6.999	20.3
66–75	11.6	7.000+	2.3
>75	4.4	No answer	12.0
Household size		City size (in 1.000)	
1 person	38.4	<10	7.8
2 persons	39.2	10–49	10.9
3 persons	12.6	50–99	5.1
4 persons	7.1	100–500	10
5+ persons	2.7	500+	66.1

5.3. Model specification

This and the subsequent section provide a detailed account of the model specification and estimation procedure for the interested reader. Latent risk of failing to access public transport is measured from responses to the question: “When using public transport, how likely are you to not make or cancel a journey, if it involves [barrier]?”. The five response options range from “highly likely” to “highly unlikely”, which means that the response variable, y_i has $C = 5$ ordered categories,

Table 3

Total counts (diagonal) of characteristics in the sample and their combinations (off-diagonals). N = 816.

	female/div.	seeing	learning	walking	autism	very tall	very small	overweight	hearing	direction
female/div.	456									
seeing	68	117								
learning	9	6	16							
walking	52	32	5	87						
autism	21	8	3	4	27					
very tall	22	12	3	8	6	71				
very small	45	19	3	11	2	0	50			
overweight	34	15	5	18	7	12	9	60		
hearing	44	29	3	21	5	6	10	11	77	
direction	75	32	6	22	8	8	15	13	14	93

where higher categories indicate a higher probability of not making or cancelling a given journey and therefore a higher risk of failing to access public transport. Levels of categorical y_i are “highly likely” (5), “likely” (4), “neither likely/nor unlikely” (3), “unlikely” (2), “highly unlikely” (1). Because responses are ordinal, we estimate a polytomous IRT model such that the response of individual i with characteristic d with respect to mobility barrier m is given by the density

$$y_{imd} = \prod_{c=1}^C \text{Prob}(y_i = c)^{I_c(y_i)} \quad (1)$$

where $I_c(y_i)$ is an indicator function, which evaluates to 1 if $y_i = c$ and to 0 otherwise. As explained in Section 4, we assume that observed ordinal response arises from the categorisation of a latent continuous variable, which can be expressed as a cumulative logistic model

$$P(y_{imd} = c) = F(\tau_c - \theta_{imd}) - F(\tau_{c-1} - \theta_{imd}) \quad (2)$$

where $F(\cdot)$ is the standard logistic distribution, $\sum_{c=1}^C \theta_c = 1$ and τ is a vector of threshold parameters of length $C - 1$ and category probability θ_{imd} where higher values indicate a higher risk of failure. Although it is possible to estimate individual or group-specific threshold parameters, we estimate overall averages, and let θ_{imd} vary by person i , where $i = 1, \dots, N$ and $N = 816$, mobility barrier m , where $m = 1, \dots, M$ and $M = 26$ mobility barriers and by characteristic d where $d = 1, \dots, D$ with $D = 10$ as follows:

$$\theta_{imd} = \alpha_i + \alpha_{m[i]} + \delta'_{md[i]} \mathbf{z}_i + \alpha_{\text{age} \times \text{gender}[i]} + \alpha_{\text{income} \times \text{city}[i]} \quad (3)$$

Survey responses are imprecise, which is why it important to distinguish between different sources of variation, so that the effect of interest can be estimated. Accordingly, α_i are random effects which vary with standard deviation σ_i and capture differences in individual latent risk of failing regardless of the type of mobility barrier individual i encounters; α_m are random effects that vary with standard deviation σ_m and capture systematic differences in latent risk of failing associated with different mobility barriers m ; α_d are random effects that vary with standard deviation σ_d and capture systematic differences in latent risk of failing between characteristics d . These random effects are correlated (see (10) to (12)), where σ_d is a $D \times 1$ vector of parameter scales and Ω is a $k \times k$ correlation matrix that follows an LKJ-distribution with shape parameter 1, which allow for correlations that are moderate in absolute value. The variable $\mathbf{z}_i$ is a $D \times 1$ vector indicating which of the possible characteristics apply to an individual. Parameters δ_{md} are a $D \times 1$ vector of random effects that varies over M mobility barriers. These parameters are the focus of this analysis. They capture the relationship between characteristics d and latent risk of failure, and they vary over mobility barriers $m = 1, \dots, M$. Thus, standard deviations $\sigma_d \forall d = 1, \dots, D$ (see (11)) captures how much the relationships of a given characteristic vary between mobility barriers.

To account for potential differences in the probability of participating in the survey, we include covariates on age, gender, income and city size. The respective combinations of random effects are $\alpha_{\text{age} \times \text{gender}}$ and $\alpha_{\text{income} \times \text{city}}$, where $\text{age} \times \text{gender}[p]$ denotes the gender-age group and $\text{income} \times \text{city}[p]$ the income-city group that person p belongs. The categories are reported in Table 2.

To complete the model specification, we specify the following hierarchical prior distributions for all parameters given in the likelihood in (1) to (3)

$$\tau_c \sim \text{Student} - t(3, 0, 2.5) \quad \forall c \in \{1, \dots, C - 1\} \quad (4)$$

$$\alpha_i \sim N(0, \sigma_i) \quad (5)$$

$$\sigma_i \sim N^+(0, 1) \quad (6)$$

$$\alpha_m \sim N(0, \sigma_m) \quad (7)$$

$$\sigma_m \sim N^+(0, 1) \quad (8)$$

$$\delta_{md} \sim N(0, \Sigma_d) \quad \forall d \in \{1, \dots, D\} \quad (9)$$

$$\Sigma = \text{diag}(\sigma_d) \times \Omega \times \text{diag}(\sigma_d) \quad (10)$$

$$\sigma_d \sim N^+(0, 3) \quad \forall d \in \{1, \dots, D\} \quad (11)$$

$$\Omega \sim \text{LKJ}(1) \quad (12)$$

$$\alpha_{\text{age} \times \text{gender}} \sim N(0, \sigma_{\text{age} \times \text{gender}}) \quad (13)$$

$$\sigma_{\text{age} \times \text{gender}} \sim \text{Student} - t^+(3, 0, 2.5) \quad (14)$$

$$\alpha_{\text{income} \times \text{city}} \sim N(0, \sigma_{\text{income} \times \text{city}}) \quad (15)$$

$$\sigma_{\text{income} \times \text{city}} \sim \text{Student} - t^+(3, 0, 2.5) \quad (16)$$

The standard deviations of the different random effects are restricted to be non-negative and follow a half Normal distribution in the case of the person random effects and half student-t distributions with 3 degrees of freedom in the case of the age-gender groups, and income-city random group effects. The scale parameter is 2.5 so as to influence results as little as possible, whilst providing some regularisation to improve convergence and sampling efficiency (Bürkner, 2017).

A consequence of using hierarchical priors is that random effects are regularised. That is, they are shrunk towards their respective population means. The amount of shrinkage in each group depends on (1) how extreme a group value in the sample is, that is, how far it is from the overall mean, and (2) how much evidence is in that group, that is, the sample size in that group. This weighting process is governed by the standard deviation, which is estimated from data. Entering parameters in the likelihood in this hierarchical fashion prevents overfitting. The implication for the estimated associations between barriers and personal characteristics is, that if a barrier severely affects users with given characteristic, but the sample contains only few respondents with this characteristic, the association will be under-estimated. The

empirical results presented here are therefore conservative in terms of the uncovered associations. At the same time, the hierarchical priors are efficient. They share information between groups with the same characteristic. Respondents with the same characteristic are expected to give somewhat similar responses to each of the survey items. Also, the hierarchical priors help disentangle the variance structure, which is particularly important in the case of repeated survey responses, where individual variation in responding to Likert-scale type questions needs to be accounted for. This way variations of interest, namely between personal characteristics and barriers can be quantified. For more information on hierarchical Bayesian modelling the interested reader is referred to Gelman (2006) and Gelman et al. (2014).

5.4. Estimation

Estimation of the joint posterior distribution, which combines likelihood and prior distributions, is performed in Stan using Markov chain Monte Carlo with sampling done via adaptive Hamiltonian Monte Carlo (Stan Development Team, 2024) and using the R package brms version 2.17 (Bürkner, 2017). The model is estimated with four independent Markov chains, with 2500 warmup iterations and 5000 sampling iterations each. Convergence in terms of stationarity of the Markov chains is checked via the split potential scale reduction factor (Rhat), which measures the ratio of the average variance of samples within each of the four chains to the variance of the pooled samples across chains. A Rhat value of 1 indicates that the four chains for a parameter are comparable to each other and therefore have converged to the same level. The reliability of estimates is further verified by looking at bulk and tail effective sample sizes (ESS), which when large indicate that estimates are reliable as they are based on a large number of independent samples from the posterior distribution.

Several model specifications were estimated and compared in terms of their goodness-of-fit. The decision which model specification best explains the data by weighing model fit against complexity was based on Pareto-smoothed importance sampling (Vehtari et al., 2017) as implemented by the R-package loo (Vehtari & Gelman, 2016). The model with the highest expected log pointwise predictive density is selected (and presented above). The distribution of observation-wise log-likelihood is investigated to check that no individual observation unduly influences the joint posterior distribution and therefore that there is no overfitting. This is the case, if all observations have k-Pareto values below 0.7.

6. Results

Parameter estimates are reported in Tables A.1–A.3. Rhat convergence diagnostics for all parameters are close to 1 indicating that MCMC chains have converged. Bulk ESS (reported) and tail effective ESS (not reported) of the marginal posterior distributions of the parameters are large. This means that parameter estimates are reliable because they are derived from a sufficiently large number of uncorrelated samples. To check how well the estimated model fits the data, Fig. 2 shows ten data sets simulated from the posterior predictive distribution (y_{rep}) which closely match with the observed data (y). Out-of-sample predictive accuracy of the estimated model can be checked by looking at the results of PSIS-LOO, which are depicted in Fig. 3. All observations have Pareto-k-values below 0.7. This means that removing any one observation from the data would have little effect on the joint posterior distribution, which in turn suggests that inferences from our model estimates are robust. Next, we look at the posterior means of the standard deviations of the varying intercepts (the threshold parameters) depicted in Fig. 4 (and reported in Table A.3). Overall, the magnitudes of the posterior means of the standard deviations highlight the importance of accounting for these different sources of variation when modelling Likert scale responses. In particular, we find that responses vary a lot across respondents as indicated by the magnitude

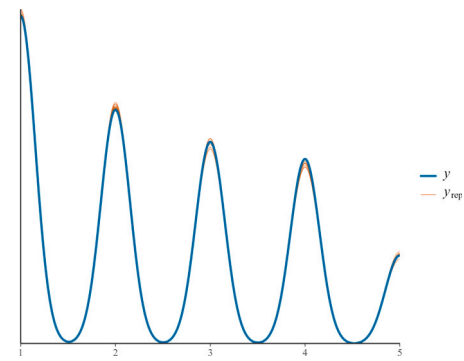


Fig. 2. Kernel density estimate of the observed data set y (blue line), with density estimates for 10 simulated data sets y_{rep} drawn from the posterior predictive distribution (orange lines).

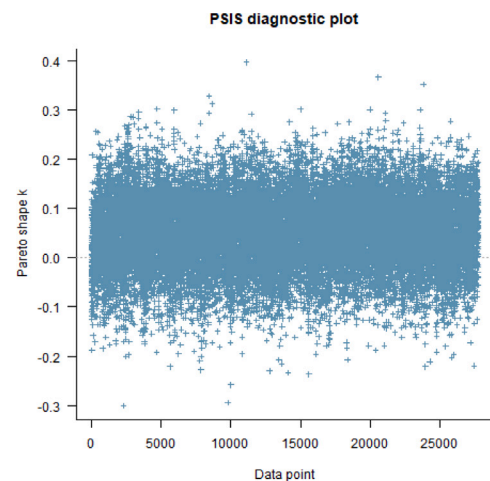


Fig. 3. Pareto-k-values for each observation.

of the estimate of the standard deviation σ_i . This suggests that different respondents use different subjective scales when answering the questions. Responses also vary a lot across mobility barriers as indicated by the magnitude of the estimate of σ_m . In fact, variation of responses is much greater between barriers than within barriers. This is expected as we presented a large number of mobility barriers, which can be more or less relevant to a given respondent with a given set of characteristics. Parameters σ_d capture variation of responses across mobility barriers within groups of respondents with the same characteristic. We find that responses vary most between those with difficulties walking, followed by those with learning difficulties and those with difficulties seeing. On the other hand, responses are quite similar for individuals who are very small and those with hearing difficulties.

Next, we discuss the results for parameters δ_{md} , which quantify associations between mobility barriers and characteristics. Posterior means are depicted in Fig. 5. They are reported in Tables A.4 to A.6 alongside their lower and upper uncertainty intervals. The figure shows if and to what extent mobility barriers (rows) are associated with different characteristics (columns) in our sample. The size of a dot indicates the magnitude of its posterior mean. The larger the dot, the larger its value and therefore the higher the risk of failing to access public transport for a person with this characteristic. The only mobility barriers for which there is no evidence of systematic associations with characteristics are air pollution and being very small or tall. Multiple dots within the same row indicate that a mobility barrier is relevant across different types of

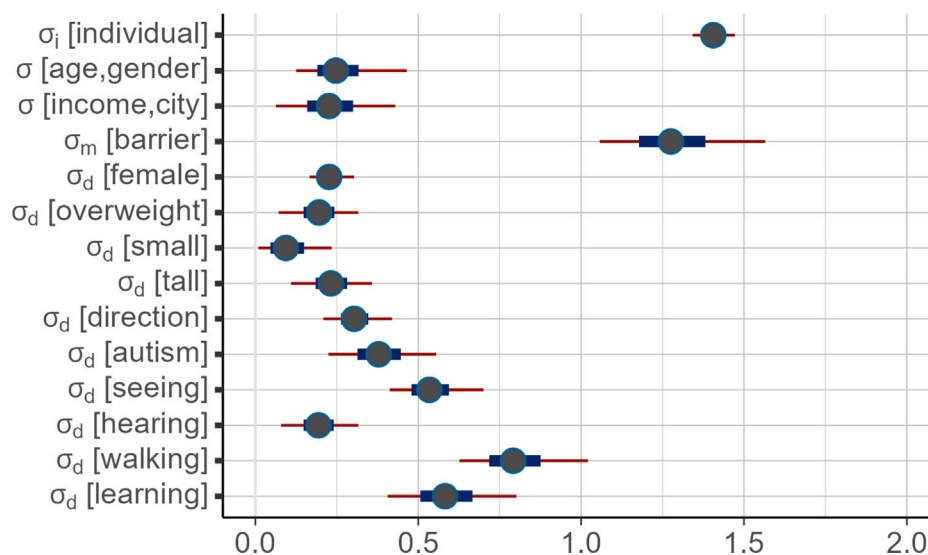


Fig. 4. Posterior distributions of the standard deviations with mode (black dot), 50% (dark blue) and 90% (light red) uncertainty interval boundaries.

characteristics. In particular, mobility barriers like escalators, stations and stops that are not accessible, missing tactile guidance and missing voice outputs are relevant to multiple characteristics. The strongest effects as indicated by their large dot sizes can be found for the mobility barriers stairs, stations and stops not being accessible, lack of help de-/boarding and toilets not being handicapped accessible. If a journey includes these mobility barriers, the risk is high that passengers with relevant characteristics will fail to make it. In our sample, the two groups who are affected by the largest number of mobility barriers are those with difficulty walking and those with learning disabilities. While most estimated correlations in our sample have uncertainty intervals that include zero, the results for the correlation matrix in Table A.3 show for these two characteristics that they are correlated and therefore work together in affecting the latent risk of failing to access public transport. Two other characteristics that are correlated in our sample are being female and being visually impaired. This correlation is also reflected in the matrix in Table 3. We find an association between being female and two mobility barriers related to being visually impaired, namely no tactile guidance systems and no voice outputs.

In conclusion, most mobility barrier are relevant for different characteristics with same mobility barriers relevant in our sample relevant to four different types of passengers. Also, as would be expected, passengers who have difficulties walking are most affected by mobility barriers, followed by passengers with learning disabilities and difficulty seeing.

7. Discussion

7.1. Survey results

This section discusses the results from the survey data analysis. When interpreting these results it has to be noted that they do not provide a representative picture of the diverse needs of public transport users in Germany. Some socio-demographic groups are over-represented, while for some characteristic, learning disabilities and autism, sample sizes too small to detect relevant associations with barriers.

First, we discuss results as they relate to the estimated interactions between mobility barriers and characteristics. In doing so it

has to be noted that information on impairments and characteristics are self-reported. Overall the estimated standard deviations show that between-group variation of latent risk of failing to access public transport is much higher, than the within-group variation. This means there are systematic differences in mobility barriers between groups of individuals who all have the same characteristic. This would be expected and shows that the focus in the previous literature on specific groups of passengers and their associated barriers is warranted. But we also find evidence that some of the same mobility barriers are relevant across different groups. In our sample, escalators, stations and stops that are not accessible, missing tactile guidance and missing voice outputs are all relevant to different groups. Based on our sample, this would suggest that alleviating these barriers would improve access across these groups of public transport users.

In terms of within-group variation, it is highest for individuals with difficulties walking, followed by those with learning difficulties and those with difficulties seeing, and it is lowest for individuals who are very small and those with hearing difficulties. High variation means that even though individuals have the same characteristic, the barriers that are relevant to them can be quite different. With regard to difficulties seeing, Engel et al. (2020) report something similar. They find that the requirements for maps and indoor aids are very different for those with low vision compared to those with blindness. In our survey, both these groups are grouped together. Thus, this within-group heterogeneity of mobility barriers that we find is also mentioned in the literature, albeit anecdotally and without being quantified. From a practical point of view, our findings highlights that knowing an individual's characteristic is not that informative about their individual risk of failing to access public transport. Arguably, refining categories that are used to describe groups may help reduce this within-group variation. But it would also increase the burden in terms of providing sensitive information and on public transport providers in terms of collecting and storing this type of data.

Next, looking at which characteristics are most affected in our survey and sample we find that those with difficulties walking have the highest number of mobility barriers. This does not necessarily mean that this group is most disadvantaged as results are conditional on the number and types of mobility barriers included in the survey. Their mobility barriers relate to seating and the design of pathways, stairs,



Fig. 5. The matrix shows associations between latent risk of failing to access public transport for all combinations of mobility barriers and characteristics. Dot size reflects the magnitude of the posterior mean of the odds ratio, $\exp(\delta_{m,d})$. Estimates are shown only of their 90 percent uncertainty interval is above 1.

escalators. This is similar to [Park and Chowdhury \(2018\)](#) who find that the main mobility barriers for physically impaired users relate to the urban environment, terminals and stops, services, and quality of footpaths; and [Neven and Ectors \(2023\)](#) who find that barriers of persons with a physical disability to be related to inter alia the inaccessibility of the public domain, public transport vehicles and stations/stops. The group that is affected by the second largest number of mobility barriers in our survey and sample are those with learning difficulties. Notable mobility barriers are “receiving travel advice via mobile phone” and “having to book tickets online”. Other mobility barriers are similar to those with difficulties walking, again due to the co-occurrence of learning and walking difficulties in our sample. The group with the third largest number of mobility barriers in our sample are those with difficulties seeing. Their mobility barriers relate to deserted stations or vehicles, and no help boarding, but also lack of tactical and vocal guidance. This is in line with work by [Park and Chowdhury \(2018\)](#) who find the main mobility barriers for visually impaired users are poor presentation of information, and obstructions on footpaths, whereas ([Engel et al., 2020](#)) also find that poor lighting conditions, missing signposting and labelling missing, unclear, too small or with little contrast and

wide areas without orientation features to be relevant mobility barriers; and [Neven and Ectors \(2023\)](#) report for persons with a visual disability, safety issues or a lack of experience, inaccessible information and orientation and inaccessible public transport vehicles as barriers.

Some of the barriers like “pricing difficult to understand” and “threatening persons” are arguably subjective. In particular because no further descriptions were provided in the survey so as to not overburden respondents. These barriers were included because experts in the focus group deemed them important. The uncovered associations in [Fig. 5](#) between autism and “pricing difficult to understand” and female and “threatening persons” can be seen as indicative of problems that may prevent members of these groups from using public transport. How to quantify these barriers is an open question and depends on data availability. Some suggestions are made in [Section 7.3](#)

The estimated correlation matrix reveals systematic co-occurrences of some of the characteristics in our sample, namely the combinations of being a woman and being visually impaired and of having difficulty walking and having a learning disability. These types of co-occurrences

in our data highlight that efforts to improve access to public transport by focusing on specific user groups may be less effective than anticipated as individuals can be members of several groups.

Because the estimation procedure incorporates regularisation (see Section 5.3), only associations that are strongly supported by the data are uncovered. Consequently, other relationships may exist that the analysis fails to detect, especially for subgroups with few observations—e.g., respondents with learning disabilities or autism. The sample is oversampled for individuals with impairments, which increases the statistical power to detect associations that would be missed in a nationally representative data set. We are not aware of population level statistics on impairments and their (co-)occurrence in the population, they tend to rare. Respondents with higher incomes are also over-represented, and income may be positively correlated with unobserved variables like “ability to afford (technological) support” or “class privilege”. These factors ease the acquisition of support for overcoming barriers, thereby making the barriers appear less severe in our results. Similarly, although people living in urban areas encounter more public transport barriers because of higher service density, they may also receive more informal assistance, as captured by the unobserved variable “support from other passengers”, something which, for example, visually impaired individuals may receive. Thus, the average associations reported in here are illustrative; they confirm that passenger requirements can, in principle, be inferred from observable barriers via the latent construct as outlined in Fig. 1. In fact, the within and between group variability of the relationships between barriers and characteristics demonstrates that relying on average associations to infer passenger requirements risks leaving some individuals without adequate access. Finally, this study shows how an IRT model can be used to quantify difficulties of items (i.e. the severity of barriers) for different individuals with different personal characteristics using survey data. In the future, if digital records of passengers (not) overcoming barriers exist, and IRT model and latent risk of failing to access public transport at a given barriers can be estimated simply based on successes and failure at barriers, without needing to know personal characteristics. This information could help public transport prioritise infrastructure upgrades or reduce customer complaints.

7.2. Benefits and limitations

Mapping passengers to mobility barriers has three benefits: privacy, actionability, and personalisation, but there are also limitations as discussed.

7.2.1. Privacy

Information about disabilities and impairments are sensitive and confidential in nature. As a result, individuals may be reluctant to provide them to transport service providers or other third parties, even if this means foregoing access to public transport. We did not find existing literature on this specific issue, but it was raised in our expert workshop. Moreover, from the point of view of transport service providers, handling these data poses an administrative burden as they require high levels of protection. This creates a hindrance to collecting and therefore using them in the first place. Instead, describing needs in the co-domain of barriers might be considered less intrusive by passengers and barrier data not considered personal data under current general data protection regularisation.

7.2.2. Actionability

For digital or public transport service providers knowing an individual's impairment or characteristics does not necessarily tell them how to modify infrastructure and vehicles or what kind of support service to offer. As the literature and also our empirical results show, within the same impairment group relevant barriers can differ. The current perspective of using personal characteristics to infer which support to offer to which group requires collecting and analysing these sensitive

data to find average associations, which may leave the individual passengers still without access. Instead, by stating barriers directly and individually, service providers receive actionable information about a given passengers' needs. The use of barrier data for secondary analysis could only be possible via opt-in procedure as a consent procurement method. These could be application-specific and even barrier-specific.

7.2.3. Personalisation

Mobility barriers vary over time, by barrier type, barrier attributes and attribute levels. For example, two individuals with difficulty walking can be quite different in their ability to use stairs (barrier type) depending on the number or height (attribute levels) of steps (barrier attribute). For example, looking at individuals with intellectual impairments or Autism Spectrum Disorder, Neven and Ectors (2023) report that some of them cycled alone without any problem, while others found it too dangerous. Accordingly, Bezyak et al. (2020) conclude that mobility barriers can be unique to an individual and vary by disability. In addition, there can be intertemporal variation of mobility barriers. For example, a stroke may cause an individual to become temporarily or persistently impaired (Asplund et al., 2012). Given the variation in mobility barriers over time and between individuals, the latter of which is quantified in this study, access is arguably better assured if passengers state the barrier that are relevant to them at given point in time.

7.2.4. Limitations

A prerequisite for the suggested focus on barriers is that data on barriers are freely available in a standardised and categorised format. Information on waiting times at stops or stations and walking distances between stops and stations are already commonly included in routing apps. With the rise of the creation of digital indoor maps, the use of crowd sourcing to enrich e.g. OpenStreetMap data, the use of sensors and the use of obstacle detection technologies, we expect more data on mobility barriers to become available in future, and Section 7.3 makes some suggestions.

Still, there are some issues we do not address in here. Some mobility barriers are easier to measure, like height difference between vehicle and platform, number of steps, step height, curb elevation, slope of ramp, which is why they are to some extent already included into OpenStreetMap (see Section 7.3). Some mobility barriers need to be quantified using sensors, like noise levels or crowding, but some mobility barriers are rather subjective. An example is “threatening people” or other attributes in relation to perceived safety. In this instances, crowd sourced reviews from apps that use barrier data to provide solutions or real-time incident alerts could be used.

7.3. Practical implementation

This section contains general considerations and ideas on how to implement a barrier data information system in the transport sector to improve accessibility.

7.3.1. Barrier data for infrastructure

Some data on barriers are already available in OpenStreetMap (OSM). There are efforts in organised editing to enrich OSM with additional barrier data. An example is an initiative by the German federal state of Baden-Wuerttemberg, which initiated organised editing of all its train stations in collaboration with the DELFI association (OSM Community Forum, 2025), which supports the development of an open public transport passenger information system. DELFI has developed their own set of barriers and barrier attributes, and they have linked them to OSM attributes. For example, the DELFI barrier “stairs” links to the OSM keys “highway = steps”, “incline”, “level”, “step:height”, “step_count” and “tactile_writing” (DELFI, 2025). In addition to OSM data, other sources for barrier data are construction drawings of stations and vehicle layouts. Also crowd sourced data, for example, for

barriers related to perceived safety at different times of day could be inferred from user-generated reviews and/or real-time or historic data on incident alerts. A data model needs to be developed to establish data exchange conventions that enable interoperability across data sets and define and standardise barriers.

Information about barriers at stations and in vehicles could also be included in the General Transit Feed Specification (GTFS) data or to Network Timetable Exchange (NeTEx), a standard for the cross-border exchange of data to enable the provision of EU-wide multi-modal travel information services. Like OSM data, they are open and widely used, thereby facilitating the scaling up of a barrier information system.

Having complete and open barrier data is a public good in the economic sense, which is why regulatory or financial incentives may be necessary to, for example, support the development of the data model as well as organised editing efforts to enrich OSM data. Public-transport operators and private companies can benefit from access to barrier data by developing APIs that deploy services to improve accessibility in general, but also for particular individuals and/or particular barriers.

7.3.2. Barrier data for passengers

Passengers' barrier data contain information about the barriers, barrier attributes and attribute levels that they want to avoid at a given point in time. They could be stored on a passenger's device. This way apps can use them in a General Data Protection Regulation compliant manner as is already the case for existing routing applications.

Given that a passenger's list of barriers can be extensive, different approaches to generate it are possible. Either a survey interface and/or chat bots elicit barrier information from passengers. This is similar (albeit more extensive) to adjusting individual setting in existing routing apps and allows making changes at any time. Or, assuming barrier data for infrastructure are complete and available, passengers could use mobile apps to update them in real time. Each encountered barrier that was insurmountable would have its type, attributes, and level logged into the passenger's barrier data.

8. Conclusion

This study uses an IRT model to compares groups of individuals with different personal characteristics in terms of their associated mobility barriers. A convenience sample is used with individuals disproportionately affected by disabilities and impairments. The results illustrate that mobility barriers and personal characteristics are systematically related via the latent construct of risk of failing to access transport. They also show that passengers with the same characteristic can be affected differently by the same mobility barrier, and a given barrier can be relevant across multiple characteristics. This means, using passenger characteristics to infer who needs what kind of support to access may still leave individuals without adequate access. Moving away from average associations for any group or characteristic, this study therefore suggests a personalised approach: individuals are directly mapped to the co-domain of barriers and to develop a privacy-respectful, actionable, and personalised barrier data information system for infrastructure. This way, a market for (digital) services offering data driven and personalised solutions for overcoming mobility barriers could be created thereby helping to improve overall access to public transport.

CRediT authorship contribution statement

Ariane Kehlbacher: Writing – review & editing, Writing – original draft, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kerstin Stark:** Writing – original draft, Resources, Project administration, Investigation, Funding acquisition, Conceptualization. **Julia Schuppan:** Funding acquisition, Conceptualization.

Table A.1

Posterior mean, lower and upper 90% percentiles, and Rhat diagnostic of random effects for different combinations of age and gender.

Intercept	Mean	l-90%CI	u-90%CI	Rhat
25–45 years, divers	0.045	−0.42	0.56	1.01
25–45 years, male	−0.297	−0.63	−0.01	1.00
25–45 years, female	0.031	−0.24	0.31	1.00
46–65 years, divers	0.098	−0.38	0.68	1.00
46–65 years, male	−0.003	−0.28	0.27	1.00
46–65 years, female	0.311	0.03	0.62	1.00
66–75 years, divers	0.055	−0.48	0.67	1.01
66–75 years, male	0.063	−0.28	0.44	1.00
66–75 years, female	0.071	−0.26	0.42	1.00
über 75 years, male	−0.150	−0.63	0.24	1.00
über 75 years, female	0.039	−0.39	0.47	1.00
unter 25 years, male	−0.096	−0.54	0.30	1.00
unter 25 years, female	−0.178	−0.66	0.21	1.00

Table A.2

Posterior mean, lower and upper 90% percentiles, and Rhat diagnostic of random effects for different combinations of monthly net household income (in Euros) and city size (in 1000).

Intercept	Mean	l-95%CI	u-90%CI	Rhat
<1.500 Euros, 10–50 inhab.	0.240	−0.12	0.78	1.00
<1.500 Euros, 100–500 inhab.	0.100	−0.28	0.57	1.01
<1.500 Euros, 50–100 inhab.	0.076	−0.35	0.60	1.00
<1.500 Euros, 500+ inhab.	−0.041	−0.35	0.23	1.00
<1.500 Euros, <10 inhab.	−0.030	−0.50	0.40	1.00
1.500 to 4.999 Euros, 10–50 inhab.	−0.126	−0.52	0.18	1.02
1.500 to 4.999 Euros, 100–500 inhab.	0.038	−0.28	0.40	1.01
1.500 to 4.999 Euros, 50–100 inhab.	0.189	−0.16	0.67	1.00
1.500 to 4.999 Euros, 500+ inhab.	−0.118	−0.38	0.09	1.01
1.500 to 4.999 Euros, <10 inhab.	0.069	−0.27	0.44	1.01
4.000 to 7.999 Euros, 10–50 inhab.	0.002	−0.40	0.39	1.00
4.000 to 7.999 Euros, 100–500 inhab.	−0.138	−0.65	0.25	1.00
4.000 to 7.999 Euros, 50–100 inhab.	−0.010	−0.50	0.47	1.01
4.000 to 7.999 Euros, 500+ inhab.	−0.295	−0.65	0.00	1.01
4.000 to 7.999 Euros, <10 inhab.	−0.087	−0.56	0.30	1.02
7.000+ Euros, 10–50 inhab.	−0.061	−0.60	0.37	1.00
7.000+ Euros, 100–500 inhab.	−0.078	−0.61	0.35	1.01
7.000+ Euros, 50–100 inhab.	−0.054	−0.61	0.40	1.00
7.000+ Euros, 500+ inhab.	0.130	−0.29	0.69	1.01
7.000+ Euros, <10 inhab.	0.114	−0.35	0.76	1.00
N/A , 10–50 inhab.	−0.114	−0.62	0.28	1.00
N/A , 100–500 inhab.	0.019	−0.45	0.50	1.00
N/A , 50–100 inhab.	−0.020	−0.50	0.43	1.01
N/A , 500+ inhab.	0.035	−0.27	0.33	1.01
N/A , <10 inhab.	0.137	−0.28	0.70	1.00

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix

See [Tables A.1–A.6](#).

Data availability

Data are available <https://mobilithek.info/offers/958748741242626048> here.

Table A.3

Posterior means of all standard deviation and correlation parameters.

	Estimate	l-95 CI	u-95CI	Rhat	Bulk ESS
$\sigma[i]$	0.263	0.10	0.52	1.01	882
$\sigma[\text{age, gender}]$	0.231	0.04	0.48	1.02	414
$\sigma[\text{income, city}]$	1.404	1.33	1.49	1.00	1721
$\sigma[\text{barrier}]$	1.285	1.02	1.63	1.00	1264
$\sigma[\text{learning}]$	0.640	0.42	0.90	1.00	4429
$\sigma[\text{walking}]$	0.813	0.61	1.09	1.00	1881
$\sigma[\text{autism}]$	0.379	0.19	0.60	1.00	4814
$\sigma[\text{hearing}]$	0.188	0.05	0.33	1.00	2851
$\sigma[\text{seeing}]$	0.544	0.40	0.74	1.00	3158
$\sigma[\text{sense of direction}]$	0.314	0.20	0.45	1.00	5758
$\sigma[\text{very tall}]$	0.256	0.11	0.40	1.00	4283
$\sigma[\text{very small}]$	0.101	0.01	0.26	1.00	3785
$\sigma[\text{overweight}]$	0.186	0.04	0.34	1.00	3494
$\sigma[\text{female}]$	0.231	0.16	0.33	1.00	5942
$\Sigma[\text{Intercept, learning}]$	-0.733	-0.91	-0.48	1.00	6140
$\Sigma[\text{Intercept, walking}]$	-0.645	-0.83	-0.39	1.00	1637
$\Sigma[\text{learning, walking}]$	0.442	0.08	0.74	1.01	1573
$\Sigma[\text{Intercept, autism}]$	0.339	-0.05	0.66	1.00	8672
$\Sigma[\text{learning, autism}]$	-0.174	-0.58	0.25	1.00	6562
$\Sigma[\text{walking, autism}]$	-0.297	-0.66	0.14	1.00	5929
$\Sigma[\text{Intercept, hearing}]$	-0.334	-0.69	0.11	1.00	6720
$\Sigma[\text{learning, hearing}]$	0.254	-0.22	0.67	1.00	6306
$\Sigma[\text{walking, hearing}]$	0.365	-0.11	0.73	1.00	7048
$\Sigma[\text{autism, hearing}]$	-0.205	-0.64	0.29	1.00	7317
$\Sigma[\text{Intercept, seeing}]$	-0.402	-0.65	-0.11	1.00	3060
$\Sigma[\text{learning, seeing}]$	0.249	-0.14	0.58	1.00	2524
$\Sigma[\text{walking, seeing}]$	0.240	-0.10	0.55	1.00	3827
$\Sigma[\text{autism, seeing}]$	-0.311	-0.68	0.11	1.00	2815
$\Sigma[\text{hearing, seeing}]$	0.282	-0.17	0.67	1.00	2319
$\Sigma[\text{Intercept, sense of direction}]$	-0.090	-0.42	0.25	1.00	6314
$\Sigma[\text{learning, sense of direction}]$	-0.095	-0.47	0.30	1.00	4035
$\Sigma[\text{walking, sense of direction}]$	-0.143	-0.50	0.24	1.00	5753
$\Sigma[\text{autism, sense of direction}]$	0.126	-0.30	0.54	1.00	4952
$\Sigma[\text{hearing, sense of direction}]$	-0.022	-0.49	0.44	1.00	4452
$\Sigma[\text{seeing, sense of direction}]$	0.268	-0.11	0.61	1.00	6939
$\Sigma[\text{Intercept, very tall}]$	0.190	-0.20	0.54	1.00	9678
$\Sigma[\text{learning, very tall}]$	-0.063	-0.47	0.37	1.00	6542
$\Sigma[\text{walking, very tall}]$	-0.188	-0.56	0.24	1.00	8404
$\Sigma[\text{autism, very tall}]$	0.151	-0.32	0.59	1.00	5544
$\Sigma[\text{hearing, very tall}]$	0.050	-0.44	0.52	1.00	4289
$\Sigma[\text{seeing, very tall}]$	-0.264	-0.64	0.17	1.00	9133
$\Sigma[\text{sense of direction, very tall}]$	-0.161	-0.57	0.28	1.00	8994
$\Sigma[\text{Intercept, very small}]$	-0.034	-0.53	0.49	1.00	15511
$\Sigma[\text{learning, very small}]$	0.010	-0.51	0.52	1.00	13819
$\Sigma[\text{walking, very small}]$	0.049	-0.49	0.55	1.00	14270
$\Sigma[\text{autism, very small}]$	0.038	-0.49	0.57	1.00	11568
$\Sigma[\text{hearing, very small}]$	0.028	-0.51	0.56	1.00	9099
$\Sigma[\text{seeing, very small}]$	-0.096	-0.60	0.44	1.00	13351
$\Sigma[\text{sense of direction, very small}]$	0.040	-0.49	0.55	1.00	12119
$\Sigma[\text{very tall, very small}]$	0.168	-0.40	0.67	1.00	8069
$\Sigma[\text{Intercept, overweight}]$	-0.274	-0.65	0.19	1.00	10052
$\Sigma[\text{learning, overweight}]$	0.103	-0.36	0.56	1.00	7856
$\Sigma[\text{walking, overweight}]$	0.442	-0.05	0.79	1.00	7663
$\Sigma[\text{autism, overweight}]$	-0.133	-0.59	0.37	1.00	9153
$\Sigma[\text{hearing, overweight}]$	0.267	-0.27	0.70	1.00	7075
$\Sigma[\text{seeing, overweight}]$	0.221	-0.26	0.64	1.00	10474
$\Sigma[\text{sense of direction, overweight}]$	0.047	-0.42	0.50	1.00	11107
$\Sigma[\text{very tall, overweight}]$	-0.192	-0.63	0.32	1.00	8863
$\Sigma[\text{very small, overweight}]$	-0.060	-0.59	0.49	1.00	7056
$\Sigma[\text{Intercept, female}]$	-0.267	-0.57	0.07	1.00	6857
$\Sigma[\text{learning, female}]$	0.128	-0.26	0.50	1.00	4087
$\Sigma[\text{walking, female}]$	0.252	-0.12	0.59	1.00	6203
$\Sigma[\text{autism, female}]$	-0.352	-0.71	0.07	1.00	4352
$\Sigma[\text{hearing, female}]$	0.208	-0.26	0.63	1.00	3506
$\Sigma[\text{seeing, female}]$	0.368	-0.01	0.68	1.00	7546
$\Sigma[\text{sense of direction, female}]$	0.009	-0.38	0.40	1.00	7965
$\Sigma[\text{very tall, female}]$	-0.185	-0.59	0.25	1.00	5023
$\Sigma[\text{very small, female}]$	-0.078	-0.58	0.46	1.00	4502
$\Sigma[\text{overweight, female}]$	0.211	-0.28	0.63	1.00	5305

Table A.4Estimated effect sizes, $\exp(\alpha_{[m,d]})$ with posterior mean and lower and upper 90% uncertainty interval estimates.

	Learning disability			Difficulty walking			Autism			Difficulty hearing		
	Mean	l-95%	u-95%	Mean	l-95%	u-95%	Mean	l-95%	u-95%	Mean	l-95%	u-95%
Air pollution at paths/stations	1.73	1.00	2.79	1.23	0.83	1.75	0.94	0.60	1.35	1.05	0.85	1.30
Audio assistance missing	1.76	0.91	2.98	1.77	1.15	2.59	0.68	0.40	1.02	1.34	1.01	1.80
Mobility barriers to access stations/stops	2.84	1.49	4.85	7.24	4.62	10.76	0.70	0.42	1.05	1.32	1.00	1.76
Car and cycling lanes not separated	1.43	0.82	2.30	1.60	1.06	2.30	0.73	0.44	1.06	1.05	0.84	1.30
Crowding in vehicles/at stations	1.32	0.74	2.17	1.26	0.82	1.82	1.65	1.04	2.59	0.99	0.79	1.21
Empty vehicles/stops	1.53	0.77	2.60	1.30	0.86	1.87	0.58	0.32	0.89	0.93	0.70	1.17
Escalators	3.78	1.96	6.60	4.23	2.70	6.15	0.72	0.42	1.08	1.09	0.84	1.38
Grubby vehicles and stops	0.71	0.39	1.13	1.20	0.80	1.71	0.96	0.62	1.37	1.07	0.86	1.33
Multiple transfers required	0.70	0.39	1.10	0.99	0.66	1.43	1.02	0.67	1.47	1.00	0.80	1.22
Narrow pathways	1.66	0.96	2.66	2.64	1.77	3.78	0.77	0.48	1.10	1.20	0.96	1.53
No aid to dis/embark	2.82	1.39	5.00	5.89	3.73	8.79	0.83	0.49	1.29	1.20	0.93	1.57
No hand holds in vehicles/ at stops	1.49	0.84	2.40	2.41	1.58	3.50	0.88	0.56	1.28	1.08	0.86	1.34
No information on transfer possibilities	0.48	0.27	0.76	0.81	0.53	1.17	1.11	0.72	1.59	1.00	0.80	1.23
No road crossings	1.80	1.02	2.98	1.62	1.07	2.34	1.01	0.65	1.47	1.05	0.84	1.30
No seating at stop	2.13	1.15	3.48	3.75	2.41	5.52	1.01	0.65	1.52	1.26	0.98	1.67
No seating in vehicle	0.78	0.43	1.25	2.41	1.56	3.58	0.83	0.51	1.21	1.09	0.86	1.37
No shelter from rain	1.24	0.70	2.03	1.35	0.90	1.93	1.12	0.74	1.61	1.04	0.84	1.30
No shelter from sun	1.86	1.05	3.09	1.03	0.69	1.47	1.19	0.78	1.77	1.05	0.85	1.30
No ticket booth/machine	0.74	0.42	1.17	0.89	0.59	1.29	1.37	0.90	2.01	0.98	0.78	1.21
No toilets in vehicles/at stations	0.99	0.57	1.54	1.70	1.14	2.43	0.93	0.61	1.31	1.09	0.89	1.36
Noise in vehicles/at stations	1.48	0.87	2.35	0.95	0.63	1.36	1.37	0.90	2.10	1.02	0.82	1.26
Online booking necessary	2.24	1.21	3.81	1.50	0.97	2.18	1.21	0.76	1.85	1.08	0.86	1.37
Other modes unavailable (e.g. taxi, bike rental)	1.79	1.01	2.87	1.31	0.88	1.87	1.04	0.68	1.50	1.17	0.94	1.51
Poorly lit paths and stops	1.18	0.63	1.93	1.95	1.28	2.85	0.81	0.51	1.19	1.13	0.90	1.43
Stairs	2.04	1.01	3.57	10.92	6.88	16.56	0.76	0.44	1.19	1.21	0.92	1.61
Stops difficult to locate	0.93	0.51	1.55	1.25	0.83	1.80	1.06	0.68	1.58	1.18	0.94	1.53
Tactile indicators missing	2.07	1.05	3.61	2.51	1.61	3.65	0.60	0.34	0.93	1.47	1.04	2.06
Threatening persons in vehicles/at stations	0.59	0.31	0.97	0.89	0.58	1.29	1.07	0.68	1.58	1.06	0.83	1.35
Ticket pricing difficult to comprehend	0.65	0.36	1.04	0.78	0.51	1.12	1.80	1.12	2.85	0.95	0.75	1.18
Toilets are not handicapped accessible	2.69	1.48	4.50	5.41	3.51	7.89	0.66	0.39	0.98	1.25	0.98	1.62
Transfer times too long	0.81	0.45	1.31	0.64	0.42	0.92	0.98	0.61	1.42	0.87	0.68	1.05
Transfer times too short	0.74	0.42	1.18	1.25	0.81	1.84	1.08	0.71	1.59	1.03	0.83	1.27
Travel advice via mobile phone	3.00	1.60	5.18	1.75	1.13	2.55	0.94	0.60	1.40	1.13	0.90	1.43
Unfamiliar modes (e.g. e-scooter)	0.66	0.35	1.12	0.81	0.52	1.20	1.22	0.76	1.88	0.88	0.65	1.10

Table A.5Estimated effect sizes, $\exp(\alpha_{\{m,d\}})$ with posterior mean and lower and upper 90% uncertainty interval estimates.

	Difficulty seeing			Poor sense of direction			Very tall			Very small		
	Mean	l-95%	u-95%	mean	l-95%	u-95%	Mean	l-95%	u-95%	Mean	l-95%	u-95%
Air pollution at paths/stations	0.82	0.57	1.14	0.70	0.51	0.92	1.27	0.96	1.67	1.03	0.89	1.23
Audio assistance missing	3.88	2.59	5.61	1.36	0.98	1.84	0.86	0.62	1.14	0.96	0.76	1.12
Mobility barriers to access stations/stops	1.87	1.27	2.64	0.87	0.62	1.18	0.87	0.62	1.16	1.01	0.84	1.20
Car and cycling lanes not separated	1.14	0.79	1.57	0.95	0.70	1.26	1.22	0.91	1.64	1.09	0.94	1.38
Crowding in vehicles/at stations	0.71	0.50	0.98	1.11	0.82	1.45	1.11	0.83	1.45	1.01	0.85	1.18
Empty vehicles/stops	2.02	1.37	2.85	1.23	0.89	1.64	0.74	0.52	1.00	0.98	0.78	1.15
Escalators	1.58	1.05	2.25	1.04	0.74	1.40	0.76	0.52	1.02	1.01	0.84	1.22
Grubby vehicles and stops	1.24	0.87	1.72	0.77	0.56	1.00	0.96	0.72	1.24	0.96	0.79	1.10
Multiple transfers required	1.16	0.80	1.62	1.42	1.05	1.89	1.04	0.79	1.36	1.04	0.91	1.26
Narrow pathways	1.39	0.96	1.94	0.90	0.67	1.18	1.18	0.89	1.57	1.03	0.89	1.22
No aid to dis/embark	2.57	1.70	3.71	1.42	1.00	1.96	0.80	0.55	1.08	1.02	0.85	1.24
No hand holds in vehicles/ at stops	1.71	1.17	2.39	1.10	0.81	1.45	0.90	0.67	1.17	1.00	0.85	1.17
No information on transfer possibilities	1.23	0.85	1.73	1.19	0.88	1.58	0.87	0.64	1.12	0.99	0.83	1.16
No road crossings	1.93	1.32	2.73	0.92	0.67	1.21	1.11	0.83	1.48	1.01	0.86	1.19
No seating at stop	1.08	0.74	1.52	0.78	0.55	1.04	1.18	0.87	1.58	1.03	0.87	1.24
No seating in vehicle	0.97	0.66	1.35	0.86	0.63	1.14	1.16	0.86	1.57	0.98	0.81	1.14
No shelter from rain	1.12	0.78	1.55	0.90	0.67	1.17	1.12	0.85	1.46	1.04	0.91	1.27
No shelter from sun	1.37	0.95	1.90	0.88	0.65	1.16	1.14	0.86	1.49	1.02	0.88	1.20
No ticket booth/machine	0.59	0.41	0.81	1.09	0.81	1.44	1.25	0.94	1.66	1.07	0.94	1.33
No toilets in vehicles/at stations	0.85	0.60	1.17	0.94	0.70	1.24	1.04	0.79	1.35	1.04	0.91	1.24
Noise in vehicles/at stations	1.30	0.90	1.81	1.10	0.82	1.44	1.07	0.81	1.39	0.99	0.84	1.14
Online booking necessary	1.12	0.76	1.56	1.36	0.99	1.85	0.90	0.64	1.18	1.00	0.84	1.18
Other modes unavailable (e g taxi, bike rental)	1.11	0.76	1.54	1.29	0.95	1.70	1.07	0.80	1.40	1.07	0.93	1.33
Poorly lit paths and stops	1.31	0.90	1.83	0.90	0.65	1.19	1.03	0.77	1.36	1.01	0.86	1.21
Stairs	0.94	0.63	1.33	0.76	0.53	1.04	0.71	0.47	0.98	1.02	0.83	1.26
Stops difficult to locate	2.00	1.38	2.79	1.57	1.15	2.10	1.01	0.76	1.33	1.05	0.89	1.28
Tactile indicators missing	4.27	2.83	6.11	1.34	0.96	1.81	0.84	0.59	1.13	0.98	0.78	1.16
Threatening persons in vehicles/at stations	0.87	0.60	1.22	0.75	0.54	1.00	1.04	0.77	1.36	0.97	0.78	1.14
Ticket pricing difficult to comprehend	0.73	0.50	1.03	1.50	1.09	2.02	1.18	0.88	1.58	1.09	0.94	1.39
Toilets are not handicapped accessible	1.90	1.29	2.68	0.94	0.68	1.25	0.84	0.60	1.11	1.00	0.84	1.19
Transfer times too long	0.75	0.52	1.05	0.86	0.63	1.12	0.92	0.69	1.17	0.96	0.78	1.10
Transfer times too short	1.37	0.94	1.92	1.14	0.84	1.51	0.88	0.65	1.14	1.02	0.88	1.19
Travel advice via mobile phone	1.23	0.83	1.73	1.03	0.74	1.37	0.96	0.70	1.27	0.99	0.82	1.14
Unfamiliar modes (e g e-scooter)	1.96	1.30	2.82	1.47	1.05	2.01	0.70	0.48	0.95	0.92	0.69	1.06

Table A.6Estimated effect sizes, $\exp(\alpha_{[m,d]})$ with posterior mean and lower and upper 90% uncertainty interval estimates.

	Overweight			Female		
	Mean	l-95%	u-95%	Mean	l-95%	u-95%
Air pollution at paths/stations	0.91	0.71	1.11	0.91	0.75	1.10
Audio assistance missing	1.23	0.95	1.64	1.35	1.08	1.68
Mobility barriers to access stations/stops	1.26	0.97	1.67	1.25	0.99	1.56
Car and cycling lanes not separated	0.93	0.72	1.13	1.18	0.96	1.44
Crowding in vehicles/at stations	1.01	0.81	1.26	1.00	0.82	1.21
Empty vehicles/stops	0.99	0.75	1.26	1.41	1.13	1.74
Escalators	1.13	0.88	1.45	1.28	1.01	1.60
Grubby vehicles and stops	1.04	0.84	1.30	0.89	0.73	1.07
Multiple transfers required	1.01	0.81	1.23	1.00	0.81	1.21
Narrow pathways	1.12	0.90	1.40	1.07	0.87	1.28
No aid to dis/embark	1.25	0.95	1.67	1.10	0.86	1.38
No hand holds in vehicles/ at stops	1.26	1.00	1.67	1.08	0.88	1.31
No information on transfer possibilities	1.04	0.83	1.30	1.10	0.89	1.34
No road crossings	1.06	0.84	1.33	1.09	0.89	1.32
No seating at stop	1.22	0.96	1.63	1.04	0.84	1.28
No seating in vehicle	1.21	0.96	1.60	1.08	0.88	1.32
No shelter from rain	1.00	0.79	1.23	0.77	0.62	0.92
No shelter from sun	0.95	0.75	1.15	0.96	0.79	1.16
No ticket booth/machine	0.99	0.79	1.22	0.81	0.66	0.98
No toilets in vehicles/at stations	1.05	0.85	1.29	0.93	0.76	1.11
Noise in vehicles/at stations	0.97	0.77	1.18	0.92	0.76	1.11
Online booking necessary	1.06	0.84	1.35	0.96	0.77	1.17
Other modes unavailable (e g taxi, bike rental)	1.01	0.80	1.24	1.04	0.85	1.26
Poorly lit paths and stops	1.14	0.90	1.45	1.61	1.30	1.99
Stairs	1.48	1.02	2.12	1.24	0.98	1.54
Stops difficult to locate	1.11	0.88	1.42	1.18	0.97	1.43
Tactile indicators missing	1.26	0.96	1.70	1.51	1.18	1.89
Threatening persons in vehicles/at stations	1.01	0.78	1.28	1.39	1.12	1.72
Ticket pricing difficult to comprehend	1.03	0.82	1.31	0.82	0.67	0.99
Toilets are not handicapped accessible	1.21	0.95	1.57	1.25	0.99	1.54
Transfer times too long	0.85	0.64	1.04	0.83	0.68	1.00
Transfer times too short	1.02	0.81	1.25	0.99	0.81	1.20
Travel advice via mobile phone	1.07	0.86	1.36	1.07	0.86	1.31
Unfamiliar modes (e g e-scooter)	1.10	0.85	1.42	1.15	0.93	1.42

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