Journal of Transport Geography 128 (2025) 104348

Contents lists available at ScienceDirect

Journal of Transport Geography

journal homepage: www.elsevier.com/locate/jtrangeo

Does a short journey get me to the food bank? An empirical study on fare-based public transport accessibility and its implications for social equity

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ARTICLE INFO

Keywords:
Accessibility
Transit
Fares
Equity
Affordability
MAUP

ABSTRACT

Fares are a critical barrier for low-income earners towards using public transport (PT). While most literature focuses only on travel time and distance, we introduce the novel indicator of 'fare accessibility'.

Fare accessibility extends *Hansen Accessibility* by incorporating pay-as-you-go costs as impedance, counting the amenity destinations reachable within a €2.30 ticket. To assess distributional equity of fare accessibility in the Greater Hamburg region (HVV) we use Lorenz curves. Furthermore, we employ spatial regression models to predict its variation based on eight factors, including PT service level, purchasing power and car availability. We calculate models at three spatial levels (municipality/PT stop/500 m grid) to discuss the influence of the Modifiable Area Unit Problem. In doing so, we assess the sensitivity and suitability of this indicator beyond established metrics.

Fare accessibility shows a significant relationship with centrality at all spatial levels. A single ticket offers the highest accessibility in densely-populated regions with a high PT service index, short travel times, low purchasing power and low car availability. While this hints towards using existing indicators at a regional level, fare accessibility helps to identify local deficits e.g. by quantifying the population without access to a food bank (which we understand as exemplary for any kind of destination). Overall, fare accessibility is less equally distributed than PT service and car availability; the HVV residents holding around half of the purchasing power are not able to reach any destination on a €2.30 budget, which is supposed to connect everyone to the next shopping centre. The share is dependent on spatial resolution, while a finer level improves sensitivity to inequity. With the Modifiable Area Unit Problem in mind, the stop level offers a suitable compromise between precision and computational capacity. Moreover, stop level analysis is compatible with practical PT planning.

Overall, fare accessibility emerges as an informative indicator for planners and policymakers. It can be expressed for numerous amenity destinations, offer insights into the daily struggles faced by low-income earners, and provide a tool to assess and improve accessibility for those most in need.

1. Introduction

There has long been a consensus that public transport accessibility is particularly relevant for marginalised groups. While most studies on this subject rely on travel time or distance, only a few include travel costs. For those affected, however, price is a much greater barrier to using public transport (PT) than travel time. Low-income earners report how they decide between a meal and a metro ticket on a daily basis (Aberle, 2023; Aberle et al., 2025; Daubitz et al., 2023; Litman, 2021) and many cope with this ever present financial struggle by spreading their travel across sporadic single rides to meet their needs (Bondemark et al., 2021; Hickey et al., 2010; Rozynek, 2024).

In this paper we introduce an index we call *fare accessibility* that we present for the HVV Greater Hamburg transport agency with a population of around 3.6 million. In contrast to conventional approaches, we calculate impedance based on pay-as-you-go fares. The result is a weighted primal index of how many amenity destinations one can reach on a €2.30 budget (Table 4). We then use spatial regressive models to predict the index by eight independent variables that describe the urban form. Furthermore, we run our models at three spatial levels to test for

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https://doi.org/10.1016/j.jtrangeo.2025.104348
Received 11 June 2024; Received in revised form 19 June 2025; Accepted 22 June 2025
Available online 8 July 2025

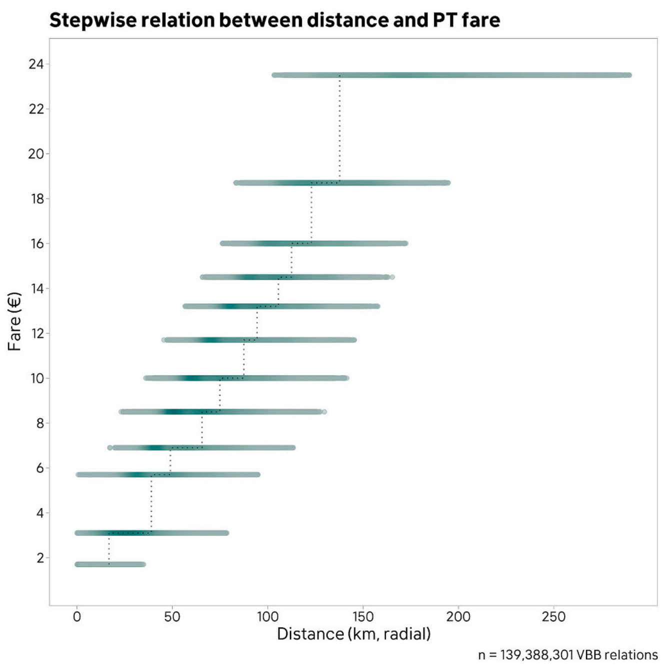

Fig. 1. Relationship between travel distance and fare in Berlin/Brandenburg transport agency (VBB). The darker the graph, the more relations are available at this price/distance combination. The dotted line shows the median distance covered by each fare above. The graph is based on data of ~139 million relations that were priced using the 2018/19 VBB fare matrix. Note that some fares <€5 are not shown to enhance readability. We show the VBB case due to data availability; a similar stepwise pattern can be assumed for most European PT systems. Da Silva et al. (2022, p. 6) plot the relationship between travel distance and fare in a comparable fashion, incorporating a regression line.

the Modifiable Area Unit Problem and identify the most suitable level, including a comparison of Gini distributions.

The data in this paper refers to the 2018/19 timetable. Since then, the German fare system has totally transformed. In summer 2022, the "9-euro ticket", enabling nationwide mobility for €9/month, was introduced as a political response to the energy crisis caused by the Russian invasion of Ukraine (Bissel, 2023). In 2023, it was consolidated into the "Deutschlandticket", which currently allows nationwide PT use for €58/month. Furthermore, 31 regions have in this period introduced a welfare discount that reduces the monthly fare, rendering the pay-as-you-go fare less relevant (Aberle, 2025a). However, despite these new affordable options, we expect single fares to remain popular with occasional travellers. Furthermore, we consider pay-as-you-go fares to continue to be relevant to those who cannot benefit from a welfare discount, such as the working poor, or those who are unable buy a "Deutschlandticket" in the first place, e.g. undocumented refugees or people without a bank account.

Fare accessibility can be quantified for any type of destination, as we do by ourselves by using a compound of 15 categories as explained in section 3.1.1. While we use food banks as an illustrative example, our paper places considerable emphasis on the underlying methodology. We aim, therefore, to fulfil three goals. First, advance transport research by describing an innovative indicator. Second, investigate the results with a focus on distributive equity and exploring the utility of intervention from a passenger's perspective. Third, apply geostatistical methods to assess the additional utility of our indicator beyond conventional travel time measures and to identify the appropriate spatial level of analysis.

2. Literature review

2.1. Accessibility-based indicators for transport poverty

Understanding *Hansen Accessibility* as potential interaction in space (Hansen, 1959; Ingram, 1971), many researchers have found that accessibility explains several qualities from employment rates over productivity to mode choice (Levinson and Wu, 2020). To account for marginalised groups, accessibility is usually combined with markers for exclusion such as unemployment rate, purchasing power or minority share, as many colleagues have pointed out at a conceptual level (e.g. Kwan, 1998; Preston and Rajé, 2007; Wachs and Kumagai, 1973) and applied in case studies (Aivinhenyo and Zuidgeest, 2019; Bocarejo and Oviedo, 2012; Chen and Wang, 2020; Da Silva et al., 2022; Delbosc and Currie, 2011; Fina et al., 2019; Guzman et al., 2017; Preston and Rajé, 2007). The risk of accessibility poverty, described by Lucas et al. (2016) as one of five components of transport poverty, is particularly high where multiple markers of exclusion compound. A recent economic analysis for Germany, for example, identified "low-income earners […] living outside the large cities who are forced to own a car due to the poor public transport service" as a particularly vulnerable group (Stark et al., 2023: 75). As illustrated by many studies, distribution measures such as the Gini coefficient and Lorenz curves are useful for describing distributive equity of accessibility (e.g. Delbosc and Currie, 2011; Ruiz-Pérez and Seguí-Pons, 2021; Chen and Wang, 2020).

2.2. Fare-based accessibility measures

While most researchers rely on travel time and some on travel distance, monetary costs are rarely used (Cui and Levinson, 2019; El-Geneidy et al., 2016; Grengs, 2015; Willberg et al., 2024) although their relevance is starting to be recognised: "For low-income populations, transit fares present a barrier to accessibility, since fares can consume a large share of individuals [sic] budget" (El-Geneidy et al., 2016: 3). However, "no study thus far has measured accessibility through including the observed cost of travel time together with the fare" (ibid., p. 7). Some attempts have been made to "*monetise*" travel time and distance into financial value (Goodwin, 1974; Liu and Kwan, 2020; Abdelwahab et al., 2021) or to "*temporalise*" the fare (Levinson and Wu, 2020: 135f; both quotations from them), with the aim of generalising travel costs (Cavallaro and Dianin, 2020; El-Geneidy et al., 2016; Liu and Kwan, 2020; Niemeier, 1997). Schlett and Loder (2025) propose a monthly index of generalised travel costs, the composition of which involves travel time and the count of traversed fare zones.

Some colleagues have combined travel time and fare without merging them into a generalised measure. By investigating the introduction of a new fare system in Greater Bogotá/Colombia, for example, Rodriguez et al. (2017) find that adding a fare threshold to their primal indicator makes workplace accessibility drop by more than 50 % compared to the travel time threshold (p. 40). Focusing on the computational feasibility, Conway and Stewart (2019) prove that it is possible to measure fare-based accessibility even in complex (i.e. path-dependent) fare systems. In addition, Da Silva et al. (2022) present an extensive analysis for seven U.S. areas. Underlining the relevance of pay-as-you-go costs, they calculate primal PT accessibility of premium commuter lines and derive the "fractional fare disparity", hereby quantifying the difference between premium and non-premium accessibility (p. 9).

Table 1
Spatial hierarchy of HVV. The three levels of investigation of this study are highlighted. PT-related data refer to the 2018/19 timetable, population data refer to December 2018. *In the meantime, the area was rearranged into eight rings, but in 2018 there were five.

HVV Greater Hamburg Transport Agency	
3	Federal states
8	Counties/Independent cities
5	Fare rings*
134	Fare zones
457	**Municipalities** (Within Hamburg: 941 Statistical regions)
7640	**PT stops**
35,193	500 m grid cells
14,586	**500 m grid cells, populated**
3,489,574	Residents

Besides these few examples, case studies on financial accessibility are rare because fare systems are difficult to model (although virtually any system should be possible with Conway and Stewart's algorithm). Further, once built and calibrated, a model is difficult to transfer to other regions, especially if several operators/agencies are involved (Aberle et al., 2024; Da Silva et al., 2022; Peter, 2021). When calculating fare accessibility for the Berlin/Brandenburg PT agency e.g. we found 21 overlapping fares of ≤€2.30. Moreover, the fare cannot be understood linearly. Most fare systems instead show a stepwise relationship between fare and distance (Fig. 1).

Recognising that most studies limit their focus to travel time, several colleagues have called for improved metrics beyond that measure (e.g. Boisjoly and El-Geneidy, 2017; Lucas, 2012). Also, Herszenhut et al. question whether travel time-based measurements are sufficient: "[N]ot addressing monetary costs explicitly [… implies] the unrealistic assumption that all individuals equally face no transport budget constraints" (Herszenhut et al., 2022: 24). Similarly, El-Geneidy et al. (2016: 3–4) suspect that a purely time-based approach may overestimate the accessibility of low-income population groups in particular. In response to improving data availiability, Willberg et al. (2024: 153) suggest expanding methods to "express [accessibility costs] through monetary, safety, health, and environmental impact". In a similar vein, Kinigadner et al. (2020) propose an accessibility indicator that builds on a carbon emission budget instead of travel time.

Through the development of more accurate metrics for a complex problem, this work provides an important advancement in transport research. We propose an indicator for primal PT accessibility based on the pay-as-you-go fare, test its sensitivity to distributive equity, compare it to established metrics and investigate how susceptible it is to the Modifiable Area Unit Problem.

2.3. The modifiable area unit problem in public transport equity research

In any spatial analysis, the resolution influences the outcome. Since the 1970s this has been referred to as *Modifiable Area Unit Problem* (MAUP; Openshaw, 1983) and has been demonstrated often (Biehl et al., 2018; Horner and Murray, 2002; Mitra and Buliung, 2012). Some colleagues have investigated how prone the equity analyses are to spatial effects, e.g. Ruiz-Pérez and Seguí-Pons (2021) who compared bus service level at four levels (neighbourhood/ census tract/cadastral block/ 400 m grid). They conclude:

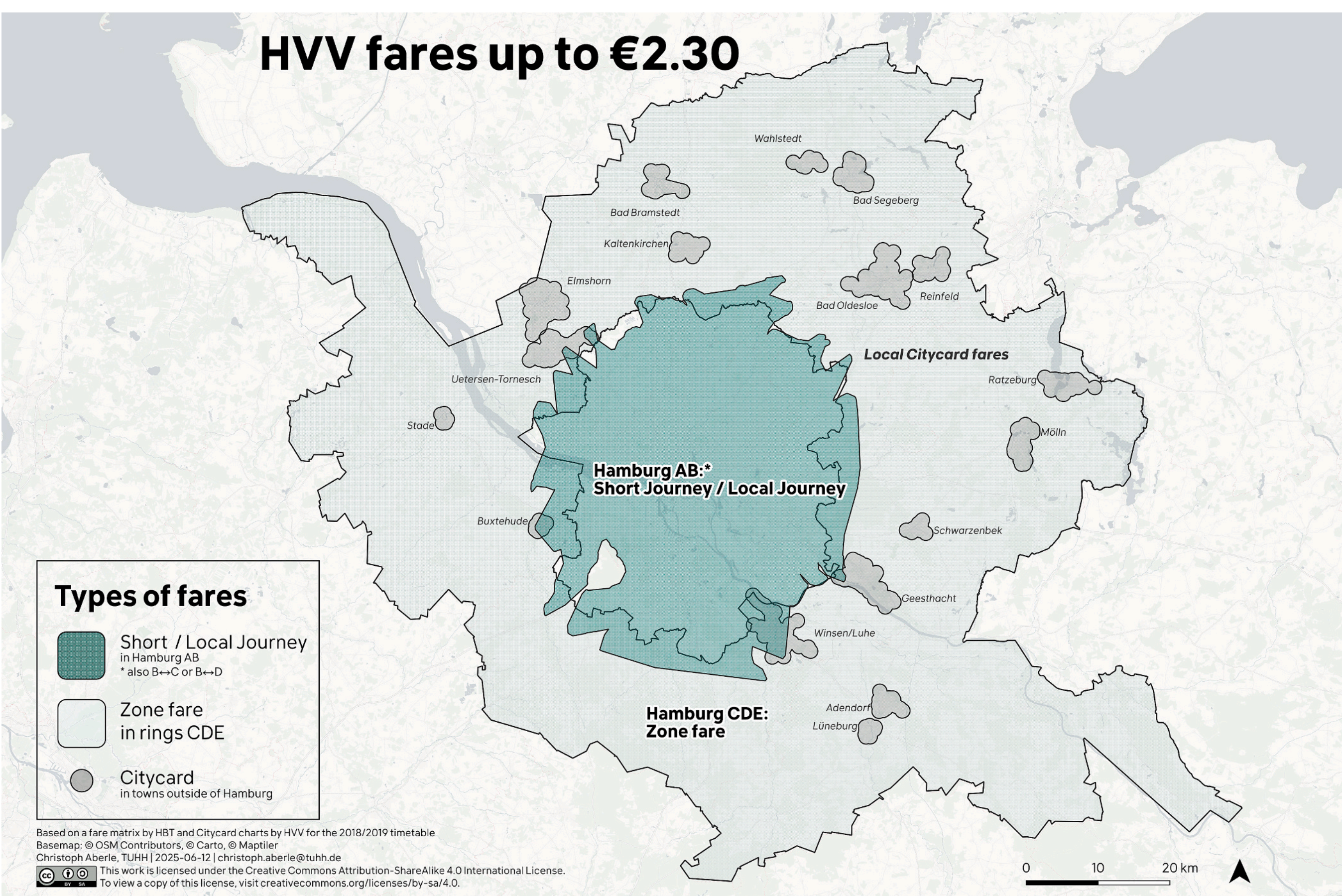

Fig. 2. Fares considered for this study. There are three types of HVV fares ≤€2.30 (Table 2). The blank area in the south-west of Hamburg AB contains a large forest that is not served by PT.

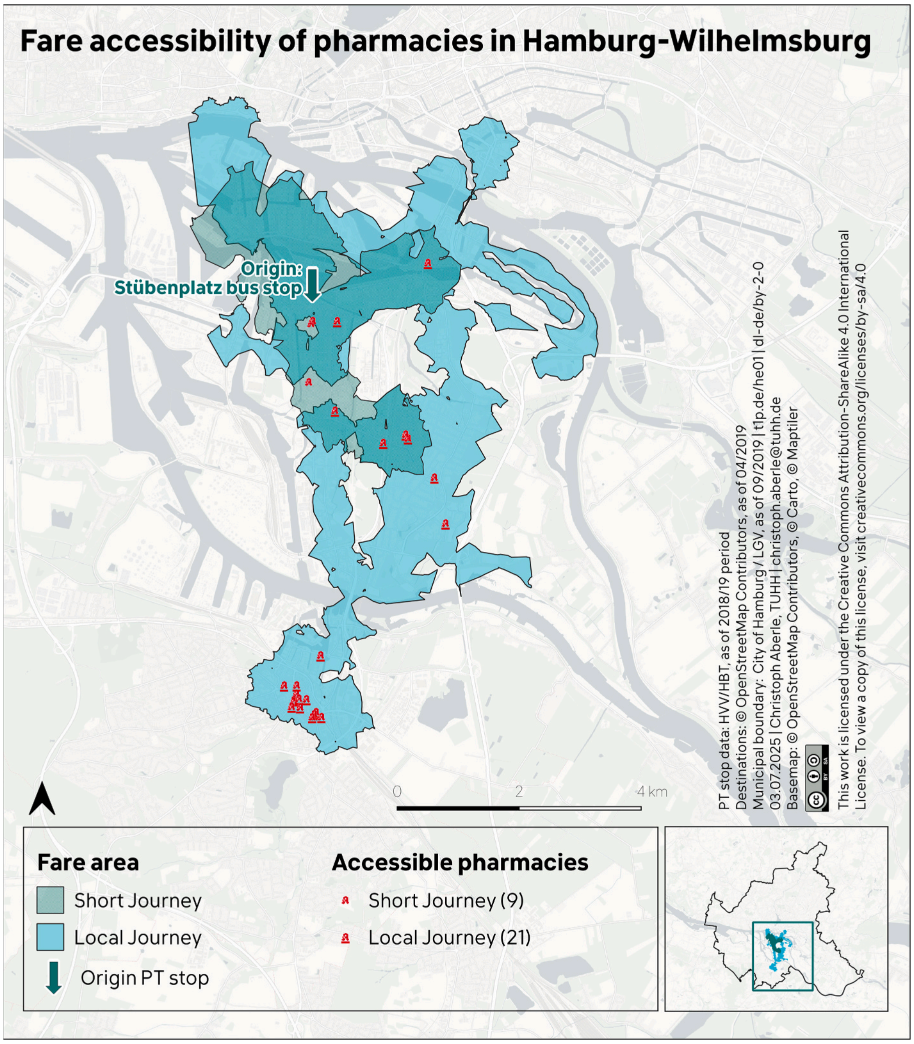

Fig. 3. Data generation process for fare accessibility. The green/dotted polygon depicts the accessible area within Short Journey (€1.70) and the blue polygon depicts the Local Journey (€2.30). To enhance readability, only pharmacies are depicted because their distribution is optimal for the purpose of the example. The two fare areas overlap because neighbouring stops partly share the same isochrone area. Destinations of each type were added together, logarithmised, normalised and then aggregated to an index across 15 categories (Table 4). Most of the destinations could be retrieved from OpenStreetMap, some were mapped manually. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

> [T]he choice of zoning has significant consequences on [the result]. […] [T]he smaller the geographical unit used, the greater the sensitivity in detecting imbalances. In other words, many imbalances could go undetected if large geographical units are used.
> (Ruiz-Pérez and Seguí-Pons, 2021: 15–18).

Similar results are described for bus pass-ups[1] in Winnipeg/Canada (Javanmard et al., 2023) and job/school accessibility in Rio de Janeiro/Brazil (Pereira et al., 2019). Following these colleagues, we compare three spatial levels: municipality, stop and 500 m grid cell. Spatial regression models are estimated at each level and the best model is determined using a sensitivity analysis (Section 3.3). Table 1 shows the three levels within the spatial hierarchy of Greater Hamburg.

[1] Pass-up: When a bus is fully occupied, the driver can't let other passengers get on. Instead, they send a message to the control centre with the bus's location.

3. Method

3.1. Calculation of fare accessibility

3.1.1. Data generation

To quantify fare accessibility, we compiled a matrix based on origin-destination data of single fares in the AB rings as provided by HVV, and complemented it by manually entering fares in the CDE rings (Fig. 2). Around each stop we drew the catchment area that can be reached on a €2.30 fare plus walking, including the origin stop (Fig. 3). We use this exact amount as a benchmark because the €2.30 Local journey fare is supposed to connect "virtually any neighbourhood to the next shopping centre in [the AB rings]" (Hamburg Parliament, 2003: 5) and marks the price for a one-zone ticket outside AB. For egress time, we assumed a maximum of 5 to 17 min, depending on the mode (bus/rail) and the spatial type of the surroundings (dense/not dense), guided by German PT standards (VDV, 2019). As opposed to the common approach of computing each singular route, we resorted to this heuristic because we worked with different PT data sets for Hamburg and Berlin/Brandenburg (the latter being the subject of the same research project). To help visualise our method, we have produced a series of interactive online maps in English (Aberle, 2020).

In PostGIS, we summed up destinations within each catchment area (Fig. 3). The generalised equation for fare accessibility is:

$$A_i(\textit{money budget}, \textit{time budget}) = \sum_j f\left(\textit{fare}_{i,j}, \textit{money budget}\right) \sum_k g\left(\textit{egress time}_{j,k}, \textit{time budget}\right)$$

such that $f\left(\textit{fare}_{i,j}, \textit{money budget}\right) \begin{cases} 1 \text{ if } \textit{fare}_{i,j} \leq \textit{money budget} \\ 0 \text{ else} \end{cases}$

and $g\left(\textit{egress time}_{j,k}, \textit{time budget}\right) \begin{cases} 1 \text{ if } \textit{egress time}_{j,k} \leq \textit{time budget} \\ 0 \text{ else} \end{cases}$

with A_i as the number of destinations that can be reached from stop *i*,
f(fare$_{i,j}$, money budget) as a function of the monetary impedance between the origin stop *i* and destination stop *j*,
which is compared with the *money budget,*
g(egress time$_{j,k}$, time budget) as a function of the temporal impedance between the destination stop *j* and the destination *k*,
which is compared with the *time budget,*
fare$_{i,j}$ as the cheapest fare on the relation from *i* to *j* in €,
money budget as available amount in €,
egress time$_{j,k}$ as the duration of the shortest walk between *j* and k in minutes and
time budget as available time in minutes.

Equation 1: Generalised equation for fare accessibility. Based on the primal indicator by Schwarze (2015: 56). A similar approach was chosen by Rodriguez et al. (2017: 38) who assumed monthly budgets.

In another step, we applied the natural logarithm to A_i to each destination category to account for the diminishing marginal utility, something that has been well-studied in economics (D'Ambrosio et al., 2020; Schumann, 1992) and has been applied in accessibility analyses in a variety of forms (Ewing et al., 2003; Henkel and Sommer, 2024; Hensher and Chen, 2010; Pereira et al., 2019). In contrast to other colleagues, we did not assign travel time-related weights as we lacked adequate data for low-income groups. In any case, a complementary survey suggests that travel time only plays a minor role for low-income urbanites (Daubitz et al., 2023). Hence, following Pereira et al. (2019: 749), we employed the logarithm. To compare different destinations, we normalised and weighted them across 15 categories (Table 4) and aggregated them. Finally, we discarded outliers beyond ±1.5 interquartile range of any variable. This common approach to data adjustment removed around 20 % of stops (and some 41 % of the HVV population in their catchment) meaning our net sample contains 5484 stops and our key indicator fare accessibility ranges between −0.09 and 0.29 standard deviations (Table 3). The net samples at the other levels are provided in the heading of Table 6; all parameters can be found in the HTML model reports in our supplementary material.

3.1.2. Aggregation at three levels

In addition to the aim of testing a novel indicator, we also wanted to assess its sensitivity at three different spatial levels, as well as its dependency on the level of analysis. Starting from stop level (1), we aggregated the median of all stops to municipality level (2). Within Hamburg (1.8 million inhabitants), we used the 941 statistical regions in order to gain units that have a population size similar to the other municipalities (∼3700 inhabitants on average). To achieve the grid level (3), we disaggregated the stop data using a *best-option* approach: for each grid cell, we obtained the highest fare accessibility among stops within 400 m (bus&tram) and 600 m (rail&metro), respectively. For districts beyond this range, the value of the nearest stop according to the OpenStreetMap network was assigned.

3.2. Four (auto-)regressive models

To assess the explanatory value of our indicator compared to common metrics, we predicted the variation of fare accessibility by eight variables of the urban form. We used four models, three of which include a spatial component to help manage spatial autocorrelation, i.e. the spillover to neighbouring regions that violates the assumption of independent residuals. Originating in ecology (Anselin and Bera, 1998), autoregressive models are increasingly used by transportation researchers e.g. to examine the influence of urban form on mode choice and environmental impact (Camagni et al., 2002; Hong et al., 2014; Hong and Shen, 2013; Mendiola et al., 2015; Travisi et al., 2006), PT accessibility of workplaces (Moniruzzaman and Páez, 2012), distributional effects of infrastructure (Pereira et al., 2019), or ride-pooling demand (Zwick, 2022). To compare the models' goodness-of-fit we followed Burkey (2018b) and Golgher and Voss (2016). The four models are nested as follows:

3.2.1. OLS: Simple linear regression

The Ordinary Least Squares model explains the variation of a dependent variable using the variation of one or more independent variables. The generalised equation is:

$$y = X\beta + \varepsilon$$

with *y* as the dependent variable in the region,
X as an independent variable in the region,
β as the regression coefficient for *X* and.
ε as error term.

Equation 2: Generalised equation for the OLS model.

3.2.2. SLX: regression with spatially-lagged X

The SLX model assumes spatial autocorrelation, i.e. that the OLS residuals are not independent, hereby violating the OLS assumptions. The SLX assumes a *spillover* from the independent variable on neighbouring regions:

$$y = X\beta + \boldsymbol{WX\theta} + \varepsilon$$

with the same parameters as Eq. 2, supplemented by.
W as the weights matrix of the independent variable *X* and.
Θ as a spatially offset effect of *X* in neighbouring regions.

Equation 3: Generalised equation for the SLX model. The addition to Eq. 2 is highlighted in bold.

3.2.3. SEM: regression with spatially-lagged error term

The SEM (*Spatial Error Model*) also assumes autocorrelation. Furthermore, it assumes a spillover of the error on the dependent variable. This does not affect the regression coefficients (i.e. β for the independent variables) but may influence the standard errors. To adjust for this effect, the SEM was developed:

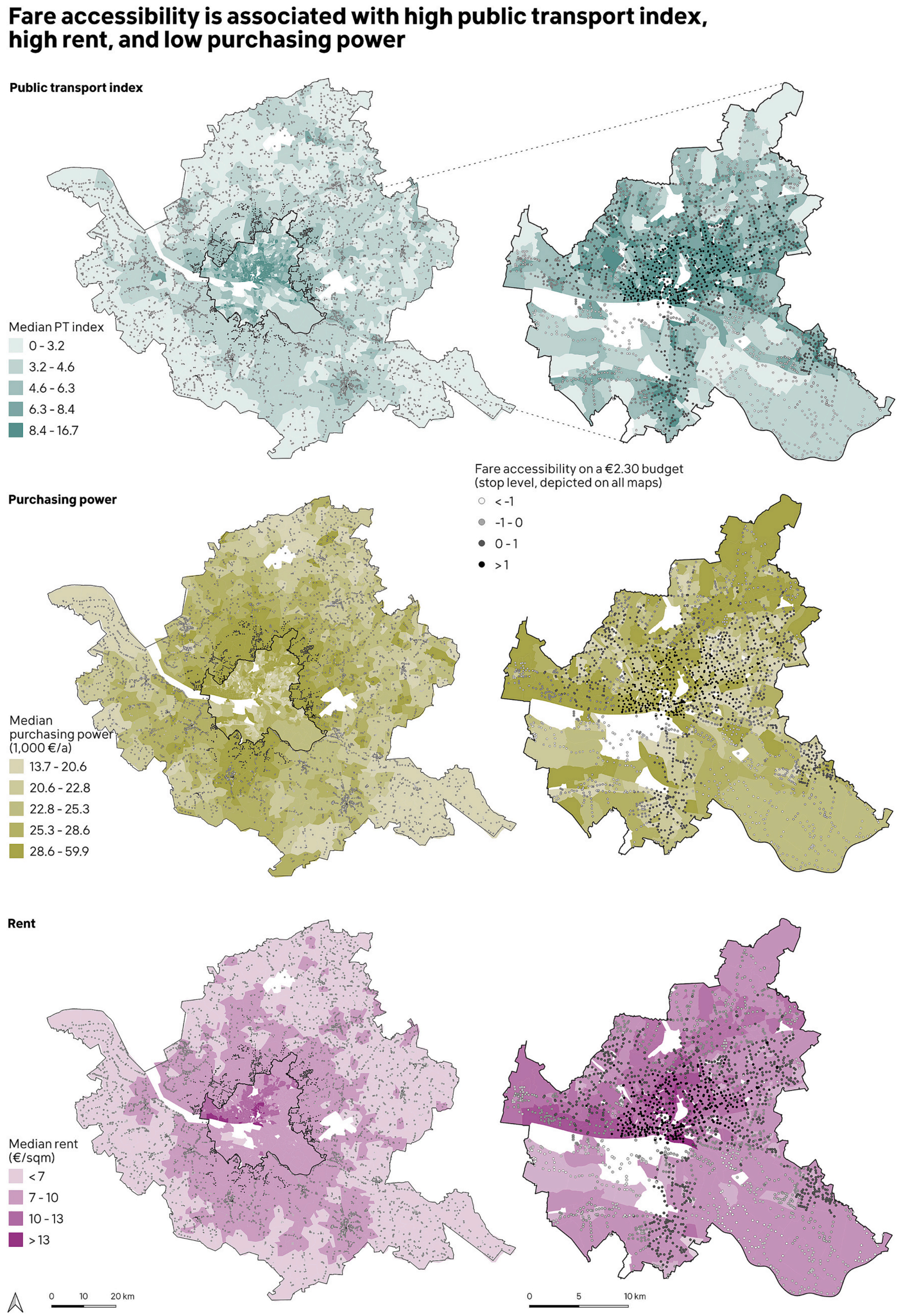

Fig. 4. Fare accessibility at stop level in comparison to social indicators at municipality level in the HVV service area (left) and in Hamburg (right). The maps reflect the highly significant correlations of fare accessibility with PT index (+), purchasing power (−), and rent (+), see Table 6.

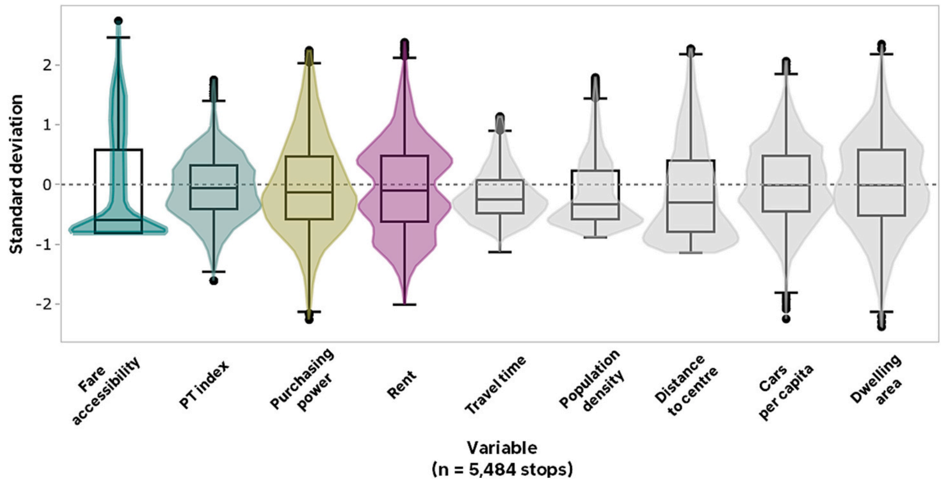

Fig. 5. Violin/box plots for the nine variables for our regressive models. The colours match the chloropleth maps in Fig. 4. Fare accessibility (dark green) shows a pronounced right-skewed distribution i.e. the mode lies below the median and some central stops show high values of > + 2SD. This also applies to population density and distance to centre, but to a smaller extent. Here we see the plausible pattern of central/peripheral regions, which might be omitted by splitting the sample in future studies.
The violin plots were compiled in R/ggplot2, using the default kernel density estimator algorithm. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

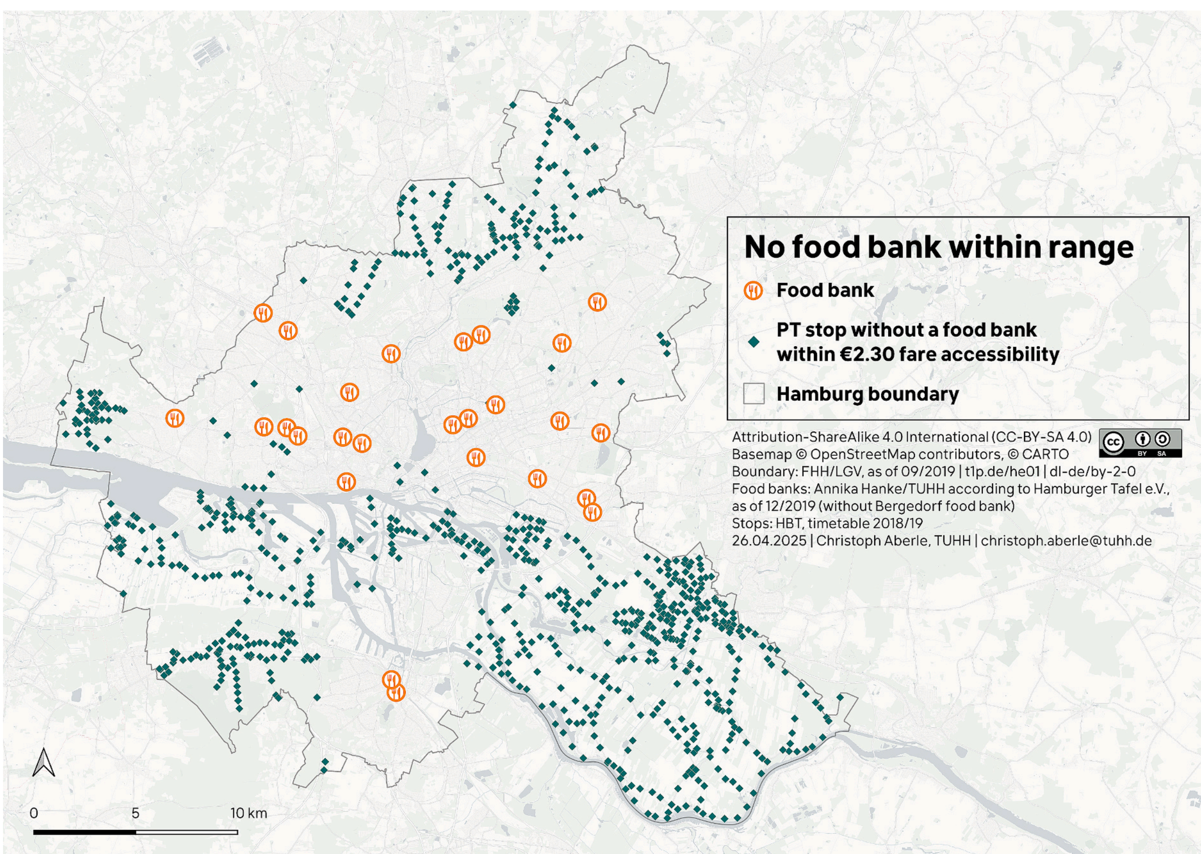

Fig. 6. Fare accessibility map for Hamburg-based food banks based on the Local Journey fare (€2.30 in 2019).

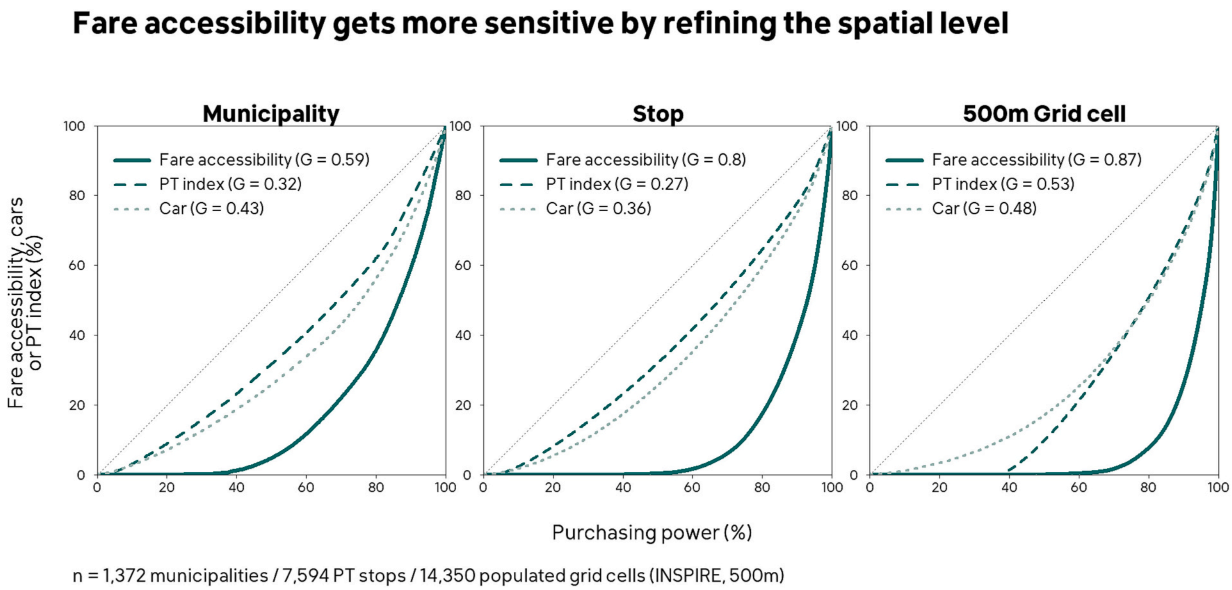

Fig. 7. Lorenz curves and Gini coefficients for fare accessibility, PT index and car availability in the HVV service area. As the solid curves show, fare accessibility becomes more sensitive between the municipality level (G = 0.59) and the grid level (G = 0.83). The +0.07 gain in precision from stop to grid level is much smaller than the gain from municipality to stop level (+0.21).
Depending on the spatial level, the fare accessibility curves rise sharply at 40–70 %. In other words, the population holding around half the purchasing power do not reach any destination on a €2.30 budget. Overall, fare accessibility is much less evenly distributed than the PT index (dashed curve) and car availability (dotted curve).

$$y = X\beta + \boldsymbol{u}$$

$$\textbf{such that } \boldsymbol{u} = \boldsymbol{\lambda W u} + \varepsilon$$

with the same parameters as Eq. 2, supplemented by.

u as the error term of the region under consideration,

λ as a spatially offset effect of the error terms of neighbouring regions and.

W as the weights matrix of the error terms.

Equation 4: Generalised equation for the SEM model. The addition to Eq. 2 is highlighted in bold.

3.2.4. *SDEM: regression with spatially offset X and error term*

The SDEM (*Spatial Durbin Error Model*) combines SLX and SEM. It assumes a spillover of the independent variable and the error term:

$$y = X\beta + \boldsymbol{WX\theta} + \boldsymbol{u}$$

$$\textbf{such that } \boldsymbol{u} = \boldsymbol{\lambda W u} + \varepsilon$$

Equation 5: Generalised SDEM equation. The addition to Eq. 2 is highlighted in bold.

The four models are nested so that the next-simplest model can be achieved by setting the added parameter zero. The models are suitable for describing local relationships, i.e. spillover to adjacent regions, as opposed to models for global relationships (Burkey, 2018c).

3.3. *Autocorrelation, sensitivity and goodness-of-fit analysis*

To identify the best data fit, we relied on four geostatistical tests and compared the (pseudo-)R^2 of the models described above.

3.3.1. *Global autocorrelation: Moran's I*

The Moran's I is a well-established test for global autocorrelation within a data set. It calculates the difference between the value predicted in the model and the observed value of a variable. This difference divided by the root of the variance of the spatial weights can be expressed as a standard deviation, which is compared with a normal distribution. Under the alternative hypothesis of spatial dependency, a significance test is carried out. If significance is given, i.e. the observed value is significantly higher than the expected one, Moran's I indicates global autocorrelation (Bivand et al., 2008: 261).

3.3.2. *Heteroscedasticity: Breusch-pagan test*

The Breusch-Pagan test measures heteroscedasticity (HST). It indicates whether the residuals depend on the independent variables, testing against the null hypothesis that there is no HST. If $p \leq 0.05$, HST has to be assumed, slightly affecting standard errors and p-values, but not the coefficients (Burkey, 2018a).

3.3.3. *Suitability of complex models: Likelihood ratio test*

The Likelihood Ratio test indicates whether it is necessary to restrict a spatial model to a less sophisticated one. If $p > 0.05$, the model should be restricted (Burkey, 2018a).

3.3.4. *Suitability of the error model: Spatial Hausman test*

The Spatial Hausman test compares SEM and OLS, testing against the null hypothesis that their parameters do not differ. If $p \leq 0.05$, it must be assumed that none of the models represent a good fit and/or that the selected error model is not suitable for capturing autocorrelation (Kelley Pace and LeSage, 2008 based on Hausman, 1978; Burkey, 2018c).

3.3.5. *Optimal spatial level: (Pseudo-)R^2*

While OLS and SLX provide a conventional R^2 (i.e., the residual sum of squares divided by the total sum of squares), the goodness-of-fit of the two error models SEM and SDEM needs to be approximated. Here, we follow Burkey (2018a) who recommends dividing the complementary of the residual sum of squares by the total sum of squares:

$$PSR^2 = \frac{1 - SS_{residual}}{SS_{total}}$$

Equation 6: Coefficient of determination that we used to approximate goodness-of-fit of the SEM and SDEM spatial error models; as recommended by Burkey (2018a).

Table 2
Most common HVV single ticket fares as of 2018/19 (HVV, 2019).

€	Fare	Validity
1.70	Short journey	Travel within one fare zone or in the inner city (Only within AB rings)
1.70	Citycard	Travel to selected stops in the town area (only in some surrounding towns, see Fig. 2)
2.30	Local journey	Travel as far as the second zone limit (only within AB rings and across the border of ring B to/from ring C or D)
2.30	1 zone	Travel as far as the first zone limit (only in CDE rings)
(3.30	Hamburg AB	Travel in the Hamburg AB rings = Greater Hamburg)

4. Results

4.1. Spatial distribution of fare accessibility

When exploring the results, a first glance at the map suggests a relationship between our indicator and the urban form: fare accessibility is characterised by a gradient from decentral to central, which resembles the distribution of e.g. PT index, purchasing power, and rent (Fig. 4). The three fare types in Fig. 2 are clearly recognisable at the stop level (Fig. 5, Table 3).

Overall, many key services are widely accessible even within the lowest fare, e.g. almost three quarters of HVV population can access a grocery store on a €1.70 Short Journey (Table 4). Food banks are less accessible; we find that only 39 % of people can reach one within a Short Journey and 56 % find one within a Local Journey range (Fig. 6, Table 4). In other words: almost half the population must pay more than €2.30 to access a food bank (one-way).

4.2. Lorenz curves at three levels

Fare accessibility is seen to be more unevenly distributed than PT index and car availability at all three levels of analysis (Fig. 7, solid curves). Concentrating on the performance in quantifying distributive equity, a major sensitivity gain is achieved by shifting from municipality level (G = 0.59) to stop level (G = 0.8). The shift to the 500 m grid level, however, yields far less sensitivity (G = 0.87).

At municipality and stop level, the dashed PT index curve is above the dotted car curve, suggesting a slightly more equitable system accessibility in terms of spatial coverage (but says very little about about accessibility in terms of e.g. travel time). On a side note, it is not a surprise to see the PT index curve at the grid level only start to rise at around 40 % of purchasing power. The cells below that point represent regions without any PT service. At the municipality level, these are evened out by the median aggregation and at the stop level they are ignored when obtaining the data within the catchment of any given stop.

4.3. Results in action: improving accessibility through fare extension

Based on the presented accessibility analysis it is even possible to estimate the opportunities that a fare-based intervention could open up for passengers that ride on a pay-as-you-go fare. An extension of the HVV Short Journey fare to the Local Journey validity, for example, would offer the potential for a significant gain in fare accessibility, as Table 5 shows: On average, stops would gain accessibility to +7.3 weighted destinations in absolute terms. With this extension, an average of +0.6 food banks could be reached. In Hamburg City this would mean + 1.9 food banks could be accessed, roughly quadruple the current choice; in the remaining HVV service area, the number of accessible food banks could be doubled (Aberle, in press, section 5.1.2.1). The distribution can also be displayed on a map, which shows a spatial disparity analogous to the stop markers in Fig. 4. Therefore, we don't present it as an extra figure.

Moreover, an intervention can be expressed in hypothetical surcharges: For the opportunity to access an additional food bank, passengers would have to spend a budget of +€1 on average. The surcharge differs strongly between the Hamburg City area (+€0.32) and the remaining HVV service area (+€6). These surcharges are of course theoretical in nature and are not reflected as such in the fare system, especially as the destinations are not logarithmised here. However, they give an impression of the stark disparity in accessibility levels between urbanized and rural areas.

The list also highlights the relevance of logarithmising and standardising the results. Without these steps, 0.9 food banks would be compared with 32 doctor's offices accessible on the Local Journey fare. The logarithm approximates the passengers' reality by sharply increasing any surplus value of another destination where there's low accessibility, while hardly assigning any added utility to stops that offer a high count of accessible amenities. Finally, normalisation ensures that the different categories can be aggregated to an index.

4.4. (Auto-)regressive models at three levels

To compare our indicator with established ones, we explained the fare accessibility variation by eight independent variables that measure

Table 3
Nine input variables for our spatial analyses. $n = 5484$ PT stops in the HVV service area. Aggregate tables for the other spatial levels can be found in the HTML model reports in the supplementary material.

VARIABLE	UNIT	MEAN	MEDIAN	SD	MIN	MAX	SOURCE	YEAR
Fare accessibility on a €2.30 budget	10 Standard deviations	−0.01	−0.07	0.09	−0.09	0.29	Own calculation, see section 3.1	12/ 2018
Average per capita purchasing power	€10,000/year	2.47	2.42	0.42	1.3	3.66	infas360	12/ 2018
Average rent	€/sqm/month, no utilities	7.81	7.74	1.29	4.47	11.97	infas360	12/ 2018
Private cars per capita	Count, approximated from street block	0.56	0.55	0.12	0.14	0.93	infas360	2018/ 19
Distance to the nearest urban centre	km, radial	3.37	2.84	2.36	0.33	10.45	Regional plans	12/ 2018
Public transport index	[no unit]	4.71	4.7	1.36	0.7	9.4	Own calculation, inspired by Delbosc and Currie (2011)	2018/ 19
Travel time to the next destination	10 min, Public transport, weighted across 15 categories similar to fare accessibility	1.71	1.58	0.7	0.14	3.84	HVV API ("GEOFOX")	12/ 2018
Population density	100 persons/ha	0.29	0.22	0.2	0.02	1	infas360	12/ 2018
Average dwelling area per capita	10 sqm	5.71	5.7	0.91	2.9	8.5	infas360	12/ 2018

Table 4
Destination categories used for the weighting of the fare accessibility indicator, and the population share that can reach the destination within Local Journey or Short Journey fare. The weighting was based on complementary interviews with 40 welfare recipients (Daubitz et al., 2023) and on previous studies (Haugen, 2011; Huber, 2016; Nordbakke and Schwanen, 2015; Schwarze, 2015). Food bank result mapped in Fig. 6 is highlighted.

Destination category	Count	Index weight (%)	Population that can reach it on a €1.70 Short Journey fare (%)	Population that can reach it on a €2.30 Local Journey fare (%)
Groceries	996	19	74	76
Doctor	1596	15	73	75
Kindergarten	1436	13	73	75
Pharmacy	743	11	75	77
Primary school	451	10	70	74
Social meeting point	181	6	51	64
Public swimming pool	48	5	40	61
Hospital	60	5	31	53
Food bank (Fig. 6)	**62**	**5**	39	56
Graveyard	175	4	37	58
Job Centre	44	3	39	56
Bookshop	174	1	56	68
Public library	222	1	59	68
Post Office	478	1	74	77
Bank	641	1	73	77
Σ	*7307*	*100*	*weighted average 64*	*71*

Table 5
Accessibility as facilitated by pay-as-you-go HVV fares up to €2.30.

	⌀ destination count as accessible by				⌀ hypothetical surcharge for more destinations	
Dest. category	Short Journey €1.70	Local Journey €2.30	Difference	Factor	Dest./ €	€/10 Dest.
Groceries	4.9	18.7	13.8	3.8	23	0.4
Doctor	8.6	32.2	23.6	3.7	39.3	0.3
Kindergarten	6.3	26.9	20.6	4.3	34.3	0.3
Pharmacy	3.7	13.6	9.9	3.7	16.5	0.6
Primary school	1.5	5.8	4.3	3.9	7.2	1.4
Social meeting point	0.7	3	2.2	4.3	3.7	2.7
Public swimming pool	0.2	0.9	0.6	4.5	1	10
Hospital	0.2	0.8	0.6	4	1	10
Food bank	0.2	0.9	0.6	4.5	1	10
Graveyard	0.4	1.6	1.2	4	2	5
Job Centre	0.3	1	0.7	3.3	1.2	8.6
Bookshop	1	3.6	2.6	3.6	4.3	2.3
Public library	1.4	5.1	3.8	3.6	6.3	1.6
Post Office	1.7	6.4	4.7	3.8	7.8	1.3
Bank	3.3	11.1	7.8	3.4	13	0.8
weighted average	*2.5*	*9.9*	*7.3*	*4*	*12.2*	*0.8*

$n = 7640$ stops, including outliers. Small deviations are due to rounding. It is noteworthy that 4280 stops do not offer a €1.70 fare (all stops outside the Hamburg AB and Citycard areas in Fig. 2).
The hypothetical surcharge was calculated by cross-multiplication, with the Local Journey costing €0.60 more than the Short Journey. For an additional €1, one can 'buy' (0.6 food banks / €0.60 · €1) one extra food bank. Reciprocally, the accessibility of ten additional food banks 'costs' around €1 (rounded to 10 cents). Similar to the fare accessibility gradient described in section 4.1, we find a palpable disparity: In Hamburg, the weighted surplus accessibility is around 50 times more 'expensive' than in the remaining HVV service area. This topic is addressed in depth by Aberle (in press, section 5.1.2.1).

qualities of the urban form (Table 3). We did so at the same three levels we used for plotting Lorenz curves and present all coefficients in Table 6. With few exceptions, the coefficients keep their sign across all levels i.e. the direction of the prediction stays the same. Furthermore, the vast majority of coefficients are at least **-significant. The coefficients with a normalised impact of $|\beta| > 0.3$ or $|\beta| > 0.5$ are highlighted in Table 6. This mainly concerns rent and travel time, the other coefficients are mostly significant but not particularly strong.

4.4.1. Regression coefficients

In the following, we elaborate the results for all three levels together, sorted by variable.

Purchasing power, one of the variables we were most interested in, has a negative impact in all models at all levels, i.e. with a €1000 increase of annual purchasing power we can expect a decrease of fare accessibility by 0.01 to 0.11 units.[2] The normalised impact, however, is not particularly strong in any model. The strongest prediction can be found in the OLS, which is the case for many other variables. At stop level, we find no significant impact for any of the three spatial models.

Rent has a significant direct impact on fare accessibility in all models and is particularly strong at stop level. A €1/sqm rent increase leads to an increase of up to 0.43 units in fare accessibility (whereas this high estimate only occurs in the unweighted OLS, which suggests autocorrelation). As the highlighted cells show, rent has the strongest influence on fare accessibility as measured by normalised impact (see our supplementary material for a normalised table). Hence, regional planners can expect rent and fare accessibility to go hand in hand.

Car availability has a ***-significant impact on fare accessibility in all but four models (two models at stop level being only *-significant, two are not significant at all). The direction is negative i.e. low car count per capita is associated with high fare accessibility. The strongest estimates are predicted by the linear models (-0.13 at grid and -1.44 at municipality level); the spatially-weighted models estimate a smaller influence (between -0.03 and -0.6), underpinning the autocorrelation diagnosis. While the impact on neighbouring regions is also ***-significant in all but one model (lag.Cars per capita), the spillover estimates are even more pronounced than those for rent. Overall, however, none of the normalised estimates exceed the $|\beta| > 0.3$ threshold. Thus, while showing a constant pattern, car availability does not predict fare accessibility as strongly as rent or travel time do. In our multivariate models, car-free living is less influential to affordable public transport than living in an area with short PT travel time to the next destination.

As expected, the **distance to the centre** also has a negative sign for fare accessibility for most of the significant coefficients. The three lagX spillover values are not constant, showing a positive β at stop level with a strong impact, while the β at other levels are negative. The SDEM lagged error model only shows a significant estimation at stop level. The coefficient of 0.4 suggests a positive impact on neighbours (the more decentral a stop is, the larger the expected fare accessibility is for neighbouring stops). Most direct and lagged coefficients, however, support the impression given by Fig. 4: a distance increase predicts a decrease of fare accessibility.

The **public transport index** shows a positive direct estimate for fare accessibility that is significant in all models. At stop level, most impacts are much stronger than at the other levels. This can probably be explained by the data generation: This level only compares stops that are

[2] To make the decimal places in the table easier to read, we multiplied the coefficients by a factor of 10 before the regression. Table 6 shows a coefficient of -1.07*** for purchasing power in the OLS, which can therefore be interpreted as 0.11. This applies to all betas in this section.

Table 6
Regression coefficients and model parameters at three spatial levels, for four models each.

Regression Coefficients by Spatial Level

Municipality n = 1 256

	SDEM	SEM	SLX	OLS
(Intercept)	5.25	12.58***	17.41***	10.66***
Purchasing power	-0.68* (0.29)	-0.40 (0.27)	-0.89* (0.41)	-1.34*** (0.39)
Rent	0.64*** (0.11)	0.22* (0.11)	0.48** (0.17)	2.64*** (0.12)
Cars per capita	-6.02*** (1.04)	-4.06*** (0.87)	-5.65*** (1.38)	-14.36*** (1.53)
Distance to centre	-0.10 (0.07)	-0.13 (0.07)	0.01 (0.11)	-0.55*** (0.10)
PT index	0.28*** (0.04)	0.26*** (0.03)	0.24*** (0.05)	0.34*** (0.05)
Travel time	-1.44*** (0.24)	-1.03*** (0.22)	-1.54*** (0.34)	-3.78*** (0.32)
Population density	-1.15 (1.84)	1.77 (1.68)	-3.59 (2.62)	0.28 (2.56)
Dwelling area	-0.19 (0.12)	0.02 (0.11)	-0.16 (0.17)	-1.36*** (0.17)
lag.Purchasing power	-0.65 (0.74)		-1.70** (0.63)	
lag.Rent	2.09*** (0.25)		2.22*** (0.22)	
lag.Cars per capita	-10.21*** (2.86)		-9.51*** (2.51)	
lag.Distance to centre	-0.18 (0.17)		-1.08*** (0.18)	
lag.PT index	0.26** (0.10)		0.02 (0.09)	
lag.Travel time	-1.48** (0.55)		-3.21*** (0.52)	
lag.Population density	-6.97 (5.03)		-3.66 (4.30)	
lag.Dwelling area	-0.75* (0.32)		-1.14*** (0.28)	
lambda	0.84*** (0.02)	0.97*** (0.01)		
Parameters	19	11	17	9
Global Moran's I				0.417***
Log Likelihood	-2913.64	-2964.90	-3306.79	
AIC (Linear model)	6649.58	7147.92	6649.58	
AIC (Spatial model)	5865.28	5951.80	6742.02	
LR test: statistic	786.30	1198.12	1035.09	
LR test: p-value	0.00	0.00	0.00	
R2			0.93	0.90
Pseudo-R2	0.97	0.97		

Stop n = 5 484

	SDEM	SEM	SLX	OLS
(Intercept)	-13.83***	-19.87***	-27.52***	-29.64***
Purchasing power	-0.28 (0.23)	-0.45 (0.23)	-0.46 (0.57)	-1.07*** (0.24)
Rent	2.03*** (0.15)	2.91*** (0.13)	2.66*** (0.30)	4.31*** (0.10)
Cars per capita	-1.75* (0.74)	-1.42* (0.67)	1.32 (1.55)	-1.23 (1.01)
Distance to centre	-0.24** (0.09)	-0.24*** (0.07)	-0.21 (0.22)	0.25*** (0.04)
PT index	0.41*** (0.06)	0.45*** (0.06)	0.61*** (0.14)	0.22* (0.09)
Travel time	-1.33*** (0.11)	-1.15*** (0.10)	-1.00*** (0.24)	-0.85*** (0.15)
Population density	7.27 (6.04)	28.59*** (5.91)	37.57** (14.47)	86.83*** (6.90)
Dwelling area	-0.24* (0.10)	-0.36*** (0.10)	0.68** (0.23)	-0.84*** (0.11)
lag.Purchasing power	-0.70 (0.36)		-0.71 (0.63)	
lag.Rent	1.23*** (0.16)		1.68*** (0.31)	
lag.Cars per capita	-4.26*** (1.16)		-2.34 (1.82)	
lag.Distance to centre	0.37** (0.12)		0.49* (0.22)	
lag.PT index	-0.03 (0.12)		-0.60*** (0.17)	
lag.Travel time	-0.95*** (0.19)		0.21 (0.28)	
lag.Population density	34.16** (10.54)		60.24*** (16.64)	
lag.Dwelling area	-0.90*** (0.15)		-1.82*** (0.26)	
lambda	0.83*** (0.00)	0.84*** (0.00)		
Parameters	19	11	17	9
Global Moran's I				0.844***
Log Likelihood	-13123.63	-13240.71	-16892.40	
AIC (Linear model)	33820.79	33913.82	33820.79	
AIC (Spatial model)	26285.27	26503.42	33939.76	
LR test: statistic	7537.52	7412.40	705.64	
LR test: p-value	0.00	0.00	0.00	
R2			0.67	0.67
Pseudo-R2	0.94	0.94		

500m Grid n = 9 073

	SDEM	SEM	SLX	OLS
(Intercept)	-4.94***	-4.77***	-20.24***	-23.29***
Purchasing power	-0.11** (0.04)	-0.05 (0.03)	-0.14 (0.08)	-0.28*** (0.08)
Rent	0.39*** (0.04)	0.38*** (0.04)	0.84*** (0.10)	3.01*** (0.05)
Cars per capita	-0.47*** (0.09)	-0.27*** (0.08)	-0.92*** (0.21)	-1.34*** (0.22)
Distance to centre	-0.30*** (0.05)	-0.37*** (0.04)	0.32** (0.11)	-0.05** (0.02)
PT index	0.10*** (0.01)	0.10*** (0.01)	0.17*** (0.03)	0.16*** (0.03)
Travel time	-0.25*** (0.03)	-0.27*** (0.03)	-0.00 (0.08)	-0.37*** (0.05)
Population density	2.87*** (0.40)	1.85*** (0.35)	3.34*** (0.93)	5.50*** (0.93)
Dwelling area	-0.09*** (0.02)	-0.05*** (0.01)	-0.06 (0.04)	-0.23*** (0.04)
lag.Purchasing power	-0.46** (0.14)		-0.88*** (0.16)	
lag.Rent	0.56*** (0.09)		2.45*** (0.11)	
lag.Cars per capita	-1.36*** (0.37)		-5.64*** (0.54)	
lag.Distance to centre	0.06 (0.08)		-0.30* (0.12)	
lag.PT index	-0.04 (0.05)		0.12* (0.06)	
lag.Travel time	-0.31** (0.10)		-0.23* (0.11)	
lag.Population density	10.60*** (1.71)		11.18*** (2.12)	
lag.Dwelling area	-0.26*** (0.06)		-0.45*** (0.07)	
lambda	0.94*** (0.00)	0.95*** (0.00)		
Parameters	19	11	17	9
Global Moran's I				0.792***
Log Likelihood	-17373.43	-17447.90	-25238.13	
AIC (Linear model)	50512.25	51286.20	50512.25	
AIC (Spatial model)	34784.86	34917.80	50640.29	
LR test: statistic	15729.40	16370.40	635.69	
LR test: p-value	0.00	0.00	0.00	
R2			0.53	0.49
Pseudo-R2	0.93	0.93		

Standardised Impact
-0.5 strongly negative
-0.3 negative
0.3 positive
0.5 strongly positive

Level of Significance
p
1 ≥ 0.05 (not significant)
1* < 0.05
1** < 0.01
1*** < 0.001

Version: ausw3
15.01.2025

served by at least one daily departure, whereas the others include regions without any service. Also, the processing of outliers influences the difference. For a data set that includes outliers (section 3.1.1), the regression coefficients are much smaller, especially at stop level. Interestingly, the SLX estimate of −0.60 at stop level in the cleaned data set suggests a lower fare accessibility for neighbouring stops. This may reflect the high number of small and overlapping fare zones in central Hamburg.[3] While not affecting the PT service level measured by the index, the zoning results in different fare accessibility among contiguous stops. Considering the global and local autocorrelation identified in section 4.3.2, the negative sign might also be an artifact that could be omitted by splitting the stops into an urban and rural data set (section 5). In any case, the direct impacts reflect the expectable outcome that a higher PT index predicts a higher number of destinations a passenger can reach on a €2.30 budget. Or, more straightforwardly: The existence of a bus service is a necessary condition for financial accessibility.

The coefficients predicting **travel time** to the next destination are negative at all levels and across all models, including the indirect impacts. Hence, a short travel time is associated with high fare accessibility, which matches the results concerning distance to the centre and PT index. The OLS at municipality level shows a β of −0.38, which equals a normalised $|\beta| > 0.3$ (highlighted in green). Like with the rent, we attribute this high impact to the autocorrelation that was identified by the tests described in section 4.3.2.

Population density significantly predicts the variation of fare accessibility in almost all models at stop and grid level with a positive sign. At municipality level, no significant impact can be observed. This is probably due to the different shape of analytical boundaries within Hamburg (918 small geographical units with a high density) in contrast to the HVV municipalities outside of Hamburg (454 larger units with a low density). This imbalance that is inherent to our data sets from different public sources could partly be mitigated by including the grid and the stop level, both of which indicate a positive association of density and fare accessibility i.e. an increase of density suggests an increase of fare accessibility. This fits in with the PT index results and also matches the well-known fact that PT needs a minimum population density to operate cost-effectively (Holtzclaw, 1994; Owen, 2004; Pushkarev and Zupan, 1982; Seskin et al., 1996).

Dwelling area shows a pattern similar to population density in a sense that at municipality level there is no impact that we can interpret reliably. The only significant impact is predicted by OLS, which is called into question due to autocorrelation and weak data-fit compared to the spatial models (section 4.3.2). At stop and grid level, we see mainly negative signs, implying an association that can be compared with purchasing power and car availability addressed above: A large dwelling area, an above-average affluence and a high number of available cars describe conditions of life that do not involve (and do not require) considerable PT fare accessibility.

When compared to the spatial models, the OLS overestimates the influence that rent, purchasing power, cars, and dwelling area exert on fare accessibility. In particular, the estimates for rent are higher by a factor of around 2–7, suggesting high autocorrelation, which can be partially compensated for by the weighted models. Overall, the lagged estimates of SLX and SDEM tend to be higher at municipality level than at the other levels in many cases. This can possibly be explained by the

[3] In the AB rings the average stop is assigned to 1.46 zones, with 27 outliers that lay within four zones. Within the other rings, the average stop is assigned to 1.06 zones. Own calculations based on 2021 data.

spatial composition of contiguity. At municipality level, the median count of adjacent regions is 6, while it is 7 at stop level and 18 at grid level. Hence, there is less potential spillover among adjacent municipalities, which are in turn more heterogenous than the stops/grid cells. This supposition is supported by the moderate Moran autocorrelation at municipality level ($I = 0.42$) and a much higher I at the other levels (>0.79, see Table 6).

4.4.2. Autocorrelation, sensitivity and goodness-of-fit analysis

As described in section 3.3, we applied common geospatial tests to assess the data and model quality. First, the Moran's I test indicates ***-significant global autocorrelation in the residuals of the OLS at all levels, hence suggests using spatial models (Table 6, "Global Moran's I"). A complementary LISA plot also shows *local* autocorrelation i.e. spatial clusters of fare accessibility in central areas (see interactive maps in the HTML model reports in our supplementary material). Secondly, the Breusch-Pagan test indicates ***-significant heteroscedasticity in the SDEM at all levels. This can influence the p-values to a small extent but does not affect the scope of the estimated parameters. Thirdly, all likelihood ratio tests suggest the spatial models to be appropriate. None of the models need to be restricted to a simpler one.

Fourthly, interestingly, the Spatial-Hausman tests at all levels call into question whether the SEM is suitable for capturing the spatial impacts, which was not the case when processing the whole data set including outliers. However, the likelihood ratio tests are ***-significant at all levels, suggesting the spatial models to be more suitable than the OLS.

Finally, the goodness-of-fit varies between an R^2 of 0.49 to 0.90 (OLS) and 0.53 to 0.93 (SLX). The pseudo-R^2 of SEM and SDEM ranges from 0.93 to 0.97. R^2 and pseudo-R^2 are not directly comparable with each other, but the explained variance of 93–97 % indicates that the models are suitable for predicting the variance of fare accessibility. For SEM and SDEM, the unexplained error variance accounts for only 3–7 %, expressing a good model fit. Overall, considering the OLS autocorrelation at all levels, the acceptable Breusch-Pagan and likelihood ratio results, the notable Spatial Hausman diagnosis and the (pseudo-)R^2, we recognise the SDEM as the model that delivers the best multivariate estimation for the variation fare accessibility in the HVV Greater Hamburg area.

5. Discussion

Our primary aim was to describe a new indicator – fare accessibility – and with it enrich the well-established *Hansen Accessibility* with a fare-based method. While the idea of using money as impendance is not entirely new (Rodriguez et al., 2017 peripherally include it for monthly fares; Conway and Stewart, 2019 prove the possibility to model complex fare systems; Aivinhenyo and Zuidgeest, 2019 measure accessibility by the share of household income spent on PT tickets), to our knowledge we are the first to measure and thoroughly discuss primal accessibility within a metropolitan region based on the lowest available pay-as-you-go fare.

The distribution of fare accessibility across the HVV area clearly reflects other properties of the urban form such as PT index, travel time, rent, car availability and purchasing power, all of which show centralised patterns. These results are in line with numerous studies that point out the interdependence of PT accessibility with urbanity as well as social indicators (e.g. Grengs, 2015; Hamidi et al., 2015; Kain, 1968; Newman and Kenworthy, 2006; Pushkarev and Zupan, 1982). Furthermore, our primal accessibility indicator quantifies the population share that cannot reach a given amenity within a monetary budget (Table 4), hereby filling a gap identified by several recent studies (El-Geneidy et al., 2016; Grengs, 2015; Willberg et al., 2024). Our results support the assumption that conventional indicators overestimate the accessibility of low-income groups (El-Geneidy et al., 2016).

Our second aim concerns distributive equity. As the Lorenz curves show, fare accessibility is distributed much more unevenly than the PT index; the Lorenz curve only rises significantly at around 50 % or higher, depending on the level of analysis (Fig. 7). In other words, the population holding half the purchasing power cannot reach any amenity destination on a €2.30 budget. Those of this group who do not have a car, i.e. 66 % of very-low-income earners (Follmer and Ruppenthal, 2025: 16), are vulnerable to accessibility poverty (Lucas et al., 2016). Table 4 reveals a share of 33 to 47 % who cannot reach an amenity destination on a Local Journey. Compared to German PT planning standards – a system should not leave more than 20 % of its population behind (VDV, 2019: 17) – the overall fare accessibility levels appear to be low.

It is also notable that fare accessibility is distributed less equitably than car availability across all levels. This makes sense because our car proxy was derived from a street block vehicle count. While there are large areas without any PT service (home to 4 % of population according to our model or 67 % when only counting rail), hardly any block exists without registered cars.

Our third aim was to discuss the utility of our indicator compared to conventional metrics by running (auto-)regressive models that include travel time accessibility and other variables of the urban form. When comparing the results, we see highly significant coefficients for most variables. In most cases, their sign is constant at all levels i.e. the direction of relationship remains. The sensitivity analyses show that the spatial models are more suitable than the linear regression model. Their (Pseudo-)R^2 between 0.53 and 0.97 indicates an explanatory value that exceeds the one provided by OLS.

Five variables predict a decrease of fare accessibility (purchasing power, cars per capita, distance to centre, travel time, dwelling area) and the remaining three variables predict an increase (rent, PT index, population density), confirming the well-investigated interdependence of PT accessibility with (low) affluence, (high) density and (high) centrality (Guzman et al., 2017; Hamidi et al., 2015; Lyons and Ewing, 2021; Newman and Kenworthy, 2006).

Concerning the MAUP, our indicator gets more sensitive when modelled at a finer spatial level, hereby confirming previous evidence that high resolutions are more suitable for capturing (lack of) accessibility (Javanmard et al., 2023; Neutens, 2015; Pereira et al., 2019; Ruiz-Pérez and Seguí-Pons, 2021). For the HVV case, the model parameters suggest the PT stop as a suitable unit of investigation, which is compatible with PT planning procedures. Moreover, the analysis at grid level demanded far more computing capacity, which is not in proportion to the result of the marginally elevated R^2.

As the regression estimates suggest, density influences fare accessibility – but far less so than rent or centrality (which are, nevertheless, closely associated with density; Ewing and Cervero, 2010; Frank et al., 2005). Thus, we encourage researchers to refine the analysis towards distinguishing the impacts of these different factors. While our study investigates an innovative method at a rather conceptual level, future researchers could emphasise its practical suitability. While we sketched a potential intervention and expressed the outcome in the form of additional accessible destinations (section 4.2), future research could investigate which interventions would help policymakers improve the accessibility of minority groups. Furthermore, future researchers could advance this work by splitting the data set into urban and non-urban subsets to account for the different PT qualities (Bae and Mayeres, 2005; Kutter, 2019).

This last point leads the discussion to methodological shortcomings, one of which is our €2.30 budget we recognise is a little biased by urbanity. The threshold follows the HVV accessibility benchmark for population within the AB rings, which are already signified by a high PT service. For dwellers outside these rings, a higher budget would probably be more realistic. For example, the next fare up of €3.30 might be meaningful for decentral areas yet is useless for the AB area where it allows for total PT accessibility, rendering any spatial analysis futile. Thus, we consider our choice of budget a useful compromise as it reflects the benchmark for the 64 % of HVV AB population while at the same time captures the €2.30 one-zone fare within the CDE rings (Table 2).

We make one other generalising assumption in the project: using the natural logarithm to describe the diminishing marginal utility when in reality the utility curve varies across destinations. As there are no survey results for low-income earners in Germany regarding their desired accessibility of 15 categories, we picked the natural logarithm as a useful compromise. In the literature we find that many analysts opt to calculate density as the population count divided by the *urbanized* area, as opposed to the total area (Holtzclaw, 1994; Newman and Kenworthy, 2006; Pushkarev and Zupan, 1982; VTA Transit, 2007). Due to data availability we refrained to the population density based on total area.

When preparing the regression data, by excluding outliers of ±1.5 interquartile range, we discarded the information for some 41 % of the HVV population. We regard this a high share and see another motivation to split the data set to retain as much information as possible. Finally, it is notable that the Spatial Hausman Test scrutinises the SEM model fit, which was not the case with a data set that included outliers.

Allowing for these caveats, we want to point out some methodological benefits: our indicator can be used to evaluate pay-as-you-go fares, which are very important in everyday life according to those affected (Aberle, 2023; Bondemark et al., 2021; Rozynek, 2024). Building on this, planners could adapt fare zones to allow key destinations to be reached within the least expensive fare. As our complementary survey suggests, a more favourable pricing scheme would likely contribute more to inclusion than a higher PT service level (Daubitz et al., 2023). Also Preston and Rajé (2007) stress the relevance of the fare for intervention:

> [T]here seems to be a built-in bias towards the provision of more public transport services (largely because of data availability). […]. Accessibility planning seems likely to exacerbate the overprovision of bus services and is unlikely to deliver the lower fares that would promote social inclusion […]. (p. 159).

Addressing the lack of data that Preston and Rajé imply here, we propose fare accessibility to fill that gap. In particular, by focusing on destination categories, we see potential for recognising and problematising deficits in PT affordability, which are extraordinarily relevant to those affected (e.g. food banks; Fig. 6).

6. Conclusions

In this study, we introduce an accessibility indicator that relies on the pay-as-you-go fare and aggregates the number of key destinations within a €2.30 one-way budget, which reflects the baseline accessibility standard for groceries in Hamburg AB. We thus extend *Hansen Accessibility* by a financial metric. Acknowledging recent methodological developments to measure equity by access to premium PT services (Da Silva et al., 2022), we consider ease of communication to be a key advantage of fare accessibility: the story of ‘not reaching a food bank on a €2.30 budget’ is likely to be more tangible to policymakers than a ratio between conventional and premium accessibility.

Our analyses contribute to transportation research in three regards. First, by exploring a new method. While there are hints at it in the literature, to our knowledge no one has yet comprehensively measured accessibility by fare and investigated its utility for urban and regional planners. Second, by discussing equity implications. We found that fare accessibility is distributed even less equally than general PT accessibility and car availability: 20 to 50 % of HVV population cannot reach any amenity destination on a €2.30 budget, leaving those in this group without access to a car, for example, open to accessibility poverty. Their deprivation, raised by low-income earners in various surveys, can now be quantified by our indicator and addressed by policymakers e.g. by the intervention that we have outlined. Finally, by setting the indicator in relation to existing key figures. Unsurprisingly, our indicator reflects other properties of the urban form such as population density, centrality, or rent. While some of these properties are certainly easier to quantify than by reverse-engineering a complex pricing scheme, our method can help identify financial exclusion from certain key destinations, as the food bank example illustrates. Further, in accordance with previous studies, we were able to replicate the Modifiable Area Unit Problem to find that inequity becomes increasingly visible when refining the level of analysis. For investigations at a regional scale, stop level seems to be most appropriate when balancing desire for precision with availability of resources.

It is the daily cost of mobility that prevents low-income earners from travelling to the amenities they need. While a body of literature agrees upon this finding, the majority of analyses remain limited to travel time. By introducing fare accessibility, we propose a measure that reconciles *Hansen Accessibility* with the day-to-day financial struggle of low-income earners. Fare accessibility helps planners to capture the risk of financial exclusion, invites researchers to investigate it further, and offers policymakers a metric to improve accessibility for those who are forced to choose between a meal and a metro ticket.

Funding

This work was supported by the German Research Foundation [grant number 382428751].

Declaration of competing interest

The authors have no competing interests to declare.

Acknowledgements

Annika Hanke, Jule Lietzau: GIS Data generation.
Stephan Daubitz, Elena Abt, Oliver Schwedes: Index weights.
Kate Monson: Proofreading.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jtrangeo.2025.104348.

Data availability

The data will be available soon, DOI: 10.15480/882.13163 (data set) as well as 10.15480/882.13162 (model reports)

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