# The importance of recurring public transport delays for accessibility and mode choice 

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## A R T I C L E I N F O

## Keywords:

Public transport
Accessibility
Travel behaviour
Delays
GTFS


#### Abstract

This paper looks at the relationship between recurring public transport delays, accessibility to jobs, and travel behaviour in the region of Scania, Sweden. The difference between potential (scheduled) accessibility, observed (actual) accessibility, and behaviour is an important part of this research. This paper contributes to the growing body of literature that uses GTFS data (for both scheduled and actual services) to provide a deeper understanding of temporal variations in accessibility with public transport. Historic public transport data were used to develop a measure for typical delays in the region. The accessibility analysis shows that, on average, recurring public transport delays result in a $4-9 \%$ reduction in accessibility to jobs in the region. The loss in accessibility varied depending on the travel time budget that was considered and the location within the region. The accessibility analysis also shows that areas with higher concentrations of households with a lower economic standard experience a smaller loss in job accessibility caused by public transport delays. However, the concentration of these effects depends on the measure that is used. The measurement of typical delays was also analysed in relation to actual trips from the regional travel survey. The statistical analysis found that recurring public transport delays were associated with a lower likelihood of using public transport compared to other motorised modes.


## 1. Introduction

### 1.1. Background

The last decade has seen the increasing integration of General Transit Feed Specification (GTFS) data into accessibility modelling (Wessel, 2019). Today its use in accessibility modelling is largely ubiquitous meaning that we can generate a more accurate picture of the accessibility conveyed by the public transport system, how this differs depending on the headway of the service, and during different time periods (see Pereira et al. (2021)). While GTFS data gives us a more dynamic and arguably much more accurate representation of accessibility by public transport (Fransen et al., 2015; Farber and Fu, 2017; Järv et al., 2018; Stępniak et al., 2019), this data is based on the planned public transport provision. As such, recurring disruptions and delays that could substantially alter this representation are not accounted for.

While many socio-economic and built-environment characteristics have been found to influence mode-choice (Schwanen and Mokhtarian,

2005; Chen et al., 2008; Van Acker and Witlox, 2011; Zhang et al., 2022), the role of recurring public transport delays in calculating accessibility and in commuter mode-choice is currently not well known. A single public transport delay may affect an individual's behaviour (e.g. mode-choice), especially if real-time travel information makes potential delays known ahead of time (see Fonzone and Schmöcker (2014); Fonzone (2015); Cats et al. (2011)). However, the expectation of a delay, because delays occur frequently between a particular origin and destination, may be more indicative of systemic issues within a transportation network and the effects may be more widespread.

The advent of real-time GTFS data and the possibility of reformatting real-time data from public transport operators allow us to reshape accessibility models so that public transport delays and deviations are accounted for in accessibility modelling. This, in turn, allows us to compare the planned to the actual public transport provision in order to understand the extent to which delays can alter the representation of accessibility by public transport that would have been produced using timetable data.

[^0]https://doi.org/10.1016/j.jtrangeo.2024.103796
Received 20 February 2023; Received in revised form 10 November 2023; Accepted 8 January 2024
Available online 13 January 2024
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### 1.2. Aim and research questions

This study seeks to generate a more nuanced representation of accessibility by public transport by including public transport delays in the models, drawing on the case of the region of Scania, Sweden. The potential relationship between these types of delays, accessibility to jobs, and commuter mode-choice are then examined.

The following research questions are posed:
RQ1. How do public transport delays affect the number of accessible jobs?

RQ2. How are these relative changes in accessibility distributed?
RQ3. Where are the accessibility losses due to delays concentrated?
RQ4. Are those that are exposed to more public transport delays less likely to use public transport?

## 2. Literature review

### 2.1. Transport justice, accessibility, and delays

In recent years, the transport justice discourse has been gaining traction, with distributive justice receiving most attention (see Pereira et al. (2017)). Several argue that accessibility is the 'good' with which we are concerned when we talk about distributive justice in transport (Martens, 2017). However, there is little consensus on how accessibility should be measured or assessed (van Wee, 2016; Miller, 2018). However, the most commonly used metric is accessibility to job opportunities (see El-Geneidy and Levinson (2022)). The advent of GTFS data has allowed for much more detailed and fine-grained analyses to be carried out. In this way, the ways in which accessibility by public transport is distributed among different groups and geographical areas can be more accurately assessed.

Several studies have also incorporated delays and actual travel times into accessibility models, seeking to capture a more 'real-to-life' picture of accessibility. If delays and deviations from travel times are not accounted for, we run the risk of overestimating accessibility by public transport (see Wessel, 2019). At the same time, given that large proportions of car-based travel exceed permitted speed limits (Swedish Transport Administration, 2019), we might at the same time be underestimating accessibility by the car. In doing so, we may not get an accurate picture of how accessibility is actually distributed among different groups and across time and space.

In one example of a study showing the uneven spatiotemporal distribution of delays, Mesbah et al. (2012) explored the operational performance of trams in Melbourne using spatial and historical analysis at a network-wide level from 2001 to 2010 . They found that roughly the south-western half of the network had improved in terms of both travel time and reliability, while the north-eastern half had deteriorated, sometimes significantly. Focusing more on the accessibility than the service provision itself, Handley et al. (2019) applied a connectivity measure including delays and transfers to a case study in Rochester, NY. They showed both 1) that connectivity and demand are linked, and 2) how accessibility in the city changed following a significant public transport network redesign. Similarly, Lee and Miller (2020) measured 'robust accessibility': places that are still accessible with a wide variety of delays, safety margins and routing alternatives, providing a conservative view of accessibility under uncertainty. They then applied this framework to a public transport investment in a neighbourhood of Cleveland, OH , to see how the robustly accessible area would grow. Focusing instead on a particular destination, Bimpou and Ferguson (2020) included the variability (measured at every 15 min in the weekday peak hours over six months for both cars and public transport) in travel times to a hospital in Glasgow into a dynamic accessibility measure, and then analysed how the reduction in accessibility caused by delays was distributed geographically.

### 2.2. Potential and observed accessibility

A key component of this paper is the exploration of the difference between potential (scheduled) accessibility, observed (actual) accessibility, and behaviour. There are two different sides to this. One side is the methodological approach that uses detailed, historic public transport data to produce more realistic accessibility analyses that use the actual public transport time stamps instead of the planned public transport schedule. The other side of this is the travel behavioural component that assesses how these deviations from the planned public transport schedule are related to mode-choice. The idea of incorporating delays into public transport accessibility modelling is not new (Wessel et al., 2017; Wessel and Farber, 2019; Liu et al., 2022). Likewise, previous research also looks at the relationship between reliability and travel behaviour and mode choice (e.g. Carrel et al. (2013)). However, our paper combines both of these approaches within a single study area.

Previous research on the topic of public transport accessibility and delays establish the idea that using GTFS data alone (scheduled trips) may not be particularly accurate and can overestimate public transport accessibility. This has been shown by Wessel et al. (2017) and then again by Wessel and Farber (2019). In both of these papers the authors question the validity of using GTFS data to model public transport accessibility because of the difference between the scheduled accessibility and the actual observed accessibility that can be measured using real-time data. However, it should be pointed out that in both of these studies, relatively short time-periods of no more than five days were used for the analysis. This means that these particular days/h were probably accurately represented within the accessibility analysis, but it remains unclear if the observed differences in accessibility were caused by public transport delays that were irregular or typical for the study areas/times. A more recent study by Liu et al. (2022) applied a similar methodology, but with a longer time-period, with similar results. These studies largely focus on the methods and provide a critique of relying on GTFS data to perform accurate public transport accessibility analyses, they do not focus on clarifying the impacts of public transport delays on accessibility. Furthermore, their results are not linked to observed travel behaviour.

Research on the topic of public transport reliability and travel behaviour often focuses on departure time instead of mode choice (Abkowitz, 1981; Bills and Carrel, 2021). While other literature considers more complex aspects of travel behaviour, it often relies on surveys (Dong et al., 2006; Carrel et al., 2013), while actually observed behaviour and its relationship to reliability remains unclear. Kaplan et al. (2014) focus more on the latter by proposing a measure which includes travel time, frequency, and delays, determining which one has the potential to accurately assess the equity of public transport provision. They applied this methodology to Copenhagen, and found that public transport provision was quite equitable in much of the city, except for the north-west 'finger'. Arbex and Cunha (2020) also aimed to improve accessibility modelling with spatiotemporal variation of delays and crowding. They used several sources of big data in São Paulo, Brazil, and estimated that delays in peak hours reduced the accessibility to jobs by about $6 \%$. While in this case excessive crowding reduced the accessibility by much more (some 57\%). This shows that delays can and do have a measurable and significant impact on (estimated) accessibility, but that other factors such as crowding can also affect the potential (scheduled) accessibility the public transport service is intended to provide.

### 2.3. Delays, customer satisfaction, and mode choice

Delays and their inverse, punctuality, are well known to be important for customer satisfaction in public transportation. van Lierop et al. (2018) conducted a literature review on the topic of public transport satisfaction. Of thirteen analysed papers, all mention either cleanliness and/or comfort as being important, eleven mention punctuality and or
reliability, ten, staff behaviour, and nine, safety. In a more recent empirical study, Bjørnson Lunke (2020) conducted a travel survey in Oslo, Norway, with some 7600 respondents, and also found that punctuality was among the most important factors, even more important than being near stations and having direct routes, especially for those with long commutes. Similarly, Monsuur (2022) studied 32,000 rail passenger survey responses in the UK and found punctuality to be a very important factor, ranking higher than both cleanliness and comfort. He also found that preferences varied among three different types of passengers (roughly: commuters, business travellers, and leisure travellers), with punctuality ranking as the most important factor for commuters, ranking as somewhat less important for business travellers, and as substantially less important for leisure travellers. While the exact ranking can vary somewhat, punctuality is thus always one of the most important factors, and delays are typically negatively associated with customer satisfaction.

With such a strong effect on customer satisfaction, it is not surprising that delays can also affect mode choice. In the Netherlands, van Loon et al. (2011) conducted a revealed preference study to investigate the link between railway reliability and the number of season-ticket holders, using data from 43 months across the whole country. The best indicator they found was the 80th minus the 50th percentile of travel time, and they estimate that a $10 \%$ improvement of this indicator leads to about $1.5 \%$ more season-ticket holders. Chakrabarti (2015) carried out a similar analysis using six months of bus data in Los Angeles, studying the links between time performance (roughly the same as punctuality) with ridership in peak hours. He estimated that an increase in punctuality of $10 \%$ would lead to about a $7.7 \%$ increase in ridership. He raised the possibility that this included a measure of well-performing bus lines cannibalising on less well-performing ones, suggesting that the whole increase is not from people transferring modes, as would be the case in the case of the Dutch season-ticket holders.

Ho et al. (2020) describe a quite comprehensive and detailed model of travel mode and time of day choice, based on data from Sydney. They estimate that the willingness to pay to reduce the standard deviation of travel time was about $25 \%$ higher for public transport than car trips, suggesting that delays are perceived as more cumbersome for some modes than others. Also comparing modes, Deka and Carnegie (2021) studied the behaviour of some 2000 passengers commuting across the Hudson river. They found that reliability and comfort appear to affect choices, as do travel time and cost. Importantly, they also find and discuss the premise that commuters are attached to the mode they are currently using, and that this limits switching to other modes, such that there is some level of inertia in the mode choice. This stickiness is something that likely occurs in other cases as well, and has likely kept the elasticities with regard to delays lower than they would otherwise have been, even if other authors have not been as explicit in discussing the effect.

## 3. Data and methods

We performed two analyses while conducting this research. One analysis looks at how recurring public transport delays affect potential accessibility to jobs. The other analysis looks at the relationship between recurring public transport delays for specific OD pairs from the travel survey and the observed mode choice and socio-demographic characteristics of each trip to work.

### 3.1. Overview of public transport in Scania

This paper and the analyses within it focus on the region of Scania, Sweden. This is the southern-most region in Sweden. Malmö is the largest city in the region and it is well-connected to Copenhagen, which is on the other side of the Öresund (or Øresund), the narrow body of water separating Sweden and Denmark. Skånetrafiken, as part of the regional authority, is the public transport authority in Scania. It is
responsible for the administration and operation of most rail and bus services in both urban and rural areas. As seen in Fig. 1, many of the rail lines connect Malmö to the other populated areas. About 43\% of the population in Scania drive a car, but also use public transport regularly while $14 \%$ of the population usually travels by public transport and $40 \%$ of the population usually travels by car (Skånetrafiken, 2019). The region is particularly fascinating because of the large proportion of the population that routinely switches between car and public transport. This means that many of the public transport users are not captive and often do have the option to use another mode. This is particularly relevant for our analyses since we are interested in the association between recurring public transport delays and modal use. This type of analysis would be largely meaningless in a system that primarily consists of captive users since they will probably not have any other choice but to simply accept the delays and arrive at their destinations later.

### 3.2. Overview of GTFS and operational data

GTFS data can be fed into a transit router, such as OpenTripPlanner or R5, in order to calculate travel times using public transport. While this data typically comes directly from public transport agencies, we created synthesised sets of GTFS data for this study. The synthesised GTFS datasets were created by reformatting operational data into the GTFS format. This means that two parallel sets of GTFS data, one with scheduled arrival and departure times and one with actual arrival and departure times could be created.

The operational data used in this analysis consisted of vehicle IDs, dates, and scheduled and actual departure and arrival times at each stop. The vehicle IDs contained information about lines and trip numbers. Therefore, it was possible to restructure the information into the GTFS format. The process of restructuring the data did not change the underlying information (which busses stop where at what time). Typically, GTFS datasets only include scheduled arrival and departure times. However, the operational data provided by the public transport provider contained both scheduled and actual arrival and departure times. Therefore, it was possible to create two parallel sets of GTFS data. Bus operational data are typically created from automatic vehicle location data with on-board GPS devices while rail operational data is typically collected from the signalling system. The public transport operator processed these data and converted them into the tables that were provided to us for this research. The operational data were thoroughly assessed and cleaned where necessary. For example, there were some instances where scheduled arrival and departure times were present, but actual arrival and departure times were not.

### 3.3. Overview of jobs data

In this analysis, jobs are used as a proxy for opportunities, which is consistent with what has been done in previous accessibility research (El-Geneidy and Levinson, 2022). The jobs data in this analysis was spatially disaggregated to 500 m grid cells. The geospatial data on jobs was extracted from Statistics Sweden's labour market register data for the year 2017 (Statistics Sweden, 2017). This dataset includes all jobs occupied by a person aged 16 or above. It is employed as a proxy for the number of jobs concentrated in a specific grid cell.

### 3.4. Overview of travel survey data

The travel survey dataset used for this study was provided by Region Skåne (Region Skåne, 2018a). The survey was conducted during Sep-tember-December 2018 among those aged 15-84 living in the Scania Region, carried out on behalf of the regional authority, Region Skåne (Enkätfabriken, 2019). The questionnaire was sent out to a random stratified sample with the intention of the sample being representative of different demographic characteristics such as gender and age, in each of the survey areas/strata. In total, 113,000 questionnaires were posted out


Fig. 1. Skånetrafiken public transport network.
with 38,164 ultimately participating in the survey. This amounted to a response rate of $34 \%$, after correcting for errors (Region Skåne, 2018). Women comprised $54 \%$ of respondents, with men comprising the remaining $46 \%$. Weights were developed to compensate for the concentration of non-response in some sociodemographic groups (Region Skåne, 2018). Respondents were asked to provide information on themselves, their mobility opportunities, their household and the trips (origin, destination, trip purpose, mode(s) used, etc.) carried out on the day in question (they were pre-assigned a day during the survey period). For this study, we have selected trips (origin-destination pairs) carried out during the time period of interest ( $5 \mathrm{am}-10 \mathrm{am}$ on weekdays) for the purpose of travelling to the workplace.

### 3.5. Accessibility estimates

A series of travel time matrices were calculated using GTFS data that were synthesised from the public transport operational data. The region of Scania was broken down into $500-\mathrm{m}$ grid cells and the centroids of these grid cells were used as the origins and destinations of the travel time matrices. From each grid cell, the travel times were calculated to every other grid cell in the region. The calculations were done using the r5r (Pereira et al., 2021) routing package, which is an interface for the R5 router using the R programming language. The analysis assumed a maximum walking distance of 800 m for station access/egress $(1600 \mathrm{~m}$ in total) and a maximum travel time of 60 min . This process was done twice, once using the synthesised (scheduled) GTFS data and once using the synthesised (actual) GTFS data. The final scheduled and actual travel times drew on estimates generated every 15 min during the morning peak for the months of October 2017 and October 2018. While there are often multiple ways to complete a public transport trip, the router
always provides the fastest travel time between each OD pair, regardless of the public transport mode that is considered (train, bus, tram, etc.). This means a faster public transport mode, such as a train, might be ignored if a trip can be completed in a shorter amount of time with a different public transport mode. These travel times were then overlaid with population and jobs data. For each grid cell, we have two measures - one with scheduled travel times and one with actual travel times - of the extent to which population and jobs can be reached within a series of time budgets. These cumulative opportunity measures were used as the basis for the accessibility analysis.

While the methods used in our paper are generally consistent with what can be seen in other research on similar topics, specifically, that is, the use of cumulative opportunity measures to analyse accessibility (Papa and Bertolini, 2015; Lee and Miller, 2022; Singh et al., 2022) and the use of GTFS data to measure public transport delays (Wessel et al., 2017; Wessel and Farber, 2019; Liu et al., 2022), we would like to highlight what we believe is an important difference between our research and other research related to public transport accessibility and reliability. This paper has a strong focus on the concept of 'recurring delays', or delays that happen not just as isolated incidents, but repeatedly over longer periods of time. This distinction is important because a measure of recurring delays should be more representative of typical public transport services and isolated delays caused by weather, traffic accidents, or a plethora of other possible reasons will not be overrepresented within the data. Larger, isolated delays are still included within the measure along with all other delays, but in the end, a median delay value is used to represent the delays. The use of a median value in the measure reduces the influence of delays that are atypical or outliers. This means that when delays are present in a recurring delay measure, they are more indicative of systemic issues. When discussing the roles
that delays and reliability play in public transport systems, and accessibility more broadly, a focus on recurring delays shifts the attention away from delays that might be perceived as random, and towards delays that are produced by systemic issues, which can be addressed by policy and design decisions.

### 3.6. Analysing the delay estimates with the travel survey data

The travel survey data (Region Skåne, 2018a) was filtered to include only work trips undertaken during the weekday peak. This amounted to approximately 6000 OD (Origin-Destination) pairs distributed throughout the region. Each OD pair corresponds with an origin statistical area and a destination statistical area. The public transport router only accepts exact point coordinates as the origins and destinations, therefore the coordinates of the public transport stop closest to the population weighted centroid of the statistical area were used for the origin and destination points. The public transport stops were used instead of the geographic centroids or the population weighted centroids in order to help ensure that the router would calculate a public transport travel time. These OD pairs serve as proxies for actual commuting trips that were observed in the regional travel survey. The corresponding statistical areas of the origin (the trip departure area, usually the home of the respondent) and the destination (the area in which the respondent's workplace is located) act as the base of the analysis. Exact departure times were not employed, but were instead compiled to the hour of the departure, for example between 07:00 and 08:00. Travel times by public transport and on foot for the OD pairs were calculated between the statistical areas in which (1) respondents' homes and (2) workplaces were located while considering the departure time that was provided in the travel survey. Two sets of travel times were calculated for each of the OD pairs, one set using the scheduled arrival/departure times, and the second set using the actual arrival/departure times. Each of these sets contained a total of four travel times. Since the departure time can vary, a measurement was taken every 15 min for the respective hours (resulting in four travel times). If a trip in the travel survey took place between 07:00 and 08:00, a travel time would be calculated using the departure times 07:00, 07:15, 07:30, and 07:45. The use of multiple departure times controls for the uncertainty of the exact departure time, and the likelihood that this can vary from day to day, and can be somewhat unreliable as they are self-reported, and thus reported differently by respondents. This process is visualised in Fig. 2. The travel survey was conducted in autumn 2018, and the differences between the scheduled and actual provision were estimated for the morning peak (05:00-10:00) for the entire month of October of the same year, complemented by the same for October 2017. This particular part of the analysis is focused on measuring what the public transport travel time between each origin point and destination point would have been had public transport been used. This is not about modelling the trips in the travel survey exactly as they might have occurred. Instead, we want to know two estimated public transport travel times (once using scheduled arrival/departure data and once using actual arrival/departure data), even if some of the OD combinations would never be made by public transport. In order to figure this out, we assumed a maximum travel time of 300 min and a maximum walking distance of 10 km . Almost nobody would actually walk multiple kilometres to make a public transport trip that takes up to 5 h , but we employed these high maximal thresholds in order for the router to still come up with a travel time for almost every OD pair, even if the trip would be unreasonable.

### 3.7. Regression modelling

The (combinations of) modes used for the OD pairs were then coded, with associations between concentrations of delays and modal use then analysed. By analysing the discrepancies between scheduled and actual public transport provision together with the modal use across the different OD pairs, we gain a more robust understanding of the
relationship between recurring delays and the use of different modes to commute to work. In this way, any observations regarding public transport punctuality can be directly compared to the behaviour of real individuals who actually travel between these origin and destination areas.

A binary logistic regression model was developed, with the associations between (1) independent variables such as: the respondent's exposure to delays; socio-economic and demographic characteristics; public transport supply in the vicinity of the respondent's home; and (2) the dependent variable of the respondent's modal use explored. This analysis was carried out in SPSS v 27. The dependent variable was tested in a number of different formats, with the final model including 'public transport' as one category and 'non-public transport motorised modes' as the reference category. The model included 6703 observations, with weights employed to counteract for underrepresentation and overrepresentation of different groups. ${ }^{1}$

A 'Potential exposure to delays by public transport indicator' variable was configured and employed as an independent variable in the analysis. This variable was configured by calculating the median delay for all OD pairs during the morning peak for the months of October 2017 and October 2018. The variable was first tested in its continuous form with an associated effect of the respondent being marginally less likely to use public transport with each increase in the delay exposure. Later, after a range of thresholds were employed, this variable was converted into and employed as a categorical variable with two categories, with the top decile of the variable (corresponding to a delay of 4 min or more) forming one category, and the remainder forming the other. This variable showed a similar effect compared to the continuous variable. Those whose home-to-workplace OD-pair was associated with delays in the top decile of delays were less likely to travel using public transport, with the magnitude of this effect much larger than with the employment of the continuous variable (see Section 4). Additionally, a 'Public transport supply indicator' was included as an independent variable. This was included in order to gain an indication of the effect of access to public transport in the model. This variable was configured by aggregating hourly departures within the area in which the respondent lives, with again, a categorical variable ultimately employed with the top decile of departures forming one category, and the remainder forming the other. Age ( $30-44$ coded as ' 1 '); gender (women ${ }^{2}$ coded as ' 1 '); household income ${ }^{3}$ ('low' (up to 30,000 SEK ${ }^{4}$ ) coded as ' 1 '); and background (born in Sweden coded as ' 1 ') were included as independent variables and produced statistically significant results in the model (at a threshold of $p$ $<0.05$ ).

## 4. Results

### 4.1. The effect of public transport delays on accessible jobs

On average, the number of jobs accessible to each person in Scania decreases by $4-9 \%$ because of public transport delays. The effects of these delays vary depending on the travel time budget that is considered. As seen in Table 1, on average, each person in Scania should be able to access about 79,500 jobs with public transport. However, when delays are considered, this number drops down to about 76,000 jobs. This means that $96 \%$ of the jobs that should be accessible are actually

[^1]

Fig. 2. Median delay calculation process.

Table 1
Average job accessibility for Scania and Malmö.

|  |  | Travel Time Budget |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- |
|  |  |  | 60 min | 45 min | 30 min |
| Scania | Accessible Jobs (Scheduled) |  | 79,431 | 46,143 | 18,438 |
|  | Accessible Jobs (Actual) |  | 75,884 | 43,113 | 16,828 |
|  | Missed Opportunities (Jobs) |  | 3547 | 3030 | 1610 |
|  | Percent Accessible (Actual/ |  | $\mathbf{9 6 \%}$ | $\mathbf{9 3 \%}$ | $\mathbf{9 1 \%}$ |
|  | Scheduled) |  |  |  |  |
| Malmönn | Accessible Jobs (Scheduled) |  | 191,121 | 128,272 | 53,320 |
|  | Accessible Jobs (Actual) |  | 185,172 | 120,830 | 48,519 |
|  | Missed Opportunities (Jobs) |  | 5949 | 7442 | 4802 |
|  | Percent Accessible (Actual/ | $\mathbf{9 7 \%}$ | $\mathbf{9 4 \%}$ | $\mathbf{9 1 \%}$ |  |
|  | Scheduled) |  |  |  |  |

accessible. When looking at a travel time budget of 30 min , we see this proportion drops to about $91 \%$. While these decreases do not seem to be too dramatic, it is important to keep in mind that the number of missed
opportunities (jobs) varies greatly depending on an individual's location, and the location(s) of the jobs he/she/they would like to access.

### 4.2. The geographical distribution of the effects of delays on accessibility

When the accessibility effects of public transport delays are shown on a map, it becomes clear that the relative reduction in accessibility to jobs caused by public transport delays is larger in town/city peripheries compared to town/city centres. Fig. 4 shows the geospatial distribution of the relative change in job accessibility in Scania. This effect can be seen most clearly in and around Malmö. More centrally located gridcells tend to be lighter shades, indicating a relatively small loss in job accessibility, and almost all of the darker shaded areas are located at the city's periphery and in the small towns that surround the city. This is likely because these suburban areas and small towns near Malmö are well-connected to a high concentration of jobs in Malmö. However, here, small delays can have a relatively large effect on the number of jobs that can be reached within the time budget. This could be due to a greater effect on connections between lines (timetable interactions). At
the same time, a small reduction in the size of the area in the city that can be reached can result in a greater number of missed opportunities (due to variations in the concentration of jobs).

This finding is also supported in the numbers. Statistics Sweden categorises each of its statistical areas as either outside of urban areas (group A), in urban areas but not centrally located (group B), or centrally located in urban areas (group C). ${ }^{5}$ Fig. 3 shows these area categories on a map. As shown in Table 2, regardless of the travel time budget, the negative effects of the delays tend to increase (in relative terms) as the areas become less urban.

### 4.3. Negative effects of delays are felt more in cities

While the relative reduction in job accessibility owing to public transport delays is worse in town peripheries compared to town centres, it is important to keep in mind that this does not tell the whole story. In these peripheral areas, there might be a large reduction in the proportion of jobs that are accessible, but there are also relatively few people affected by these delays and loss of job accessibility. This means that taking a weighted approach that multiplies the number of missed jobs by the number of people who miss out on these potential opportunities due to public transport delays can give a more accurate representation of the distribution of the effects of these delays throughout the population. If we look at the geographic distribution of these missed 'person-jobs', we see that these effects are mostly felt in cities. This can be seen in Fig. 5. There is an important distinction between this finding and the previous one. The previous finding is purely focused on geography and how the delays are distributed through space. People are not considered. This finding is instead focused on where people who are affected by delays are geographically distributed.

### 4.4. Areas with greater proportions of people living in a household with a low economic standard are less exposed to delays

In general, Table 3 shows that areas with higher concentrations of households living with a lower economic standard ${ }^{6}$ experience a smaller loss in job accessibility caused by public transport delays. As with the other results, this also varies depending on the travel time budget considered. Quintile 1 corresponds with areas that are occupied by the lowest concentrations of people living with a lower economic standard and quintile 5 corresponds with areas that are occupied by the highest concentrations of people living with lower economic standards. When the travel time budget of 45 min is considered, people living in quintile 1 can reach $88 \%$ of the jobs that they should be able to reach with public transport while people living in quintile 5 can reach $94 \%$ of the jobs that they should be able to reach with public transport. There are two factors that could potentially be affecting this. There tend to be higher concentrations of people living with lower economic standards in urban areas, where the relative reduction in job accessibility is lowest, likely due to the high concentrations of jobs and public transport services in these areas. Additionally, wealthier people who are less reliant on public transport might be self-selecting and choosing to live in suburban areas

[^2]that are more car dependent and have less access to public transport, which could perhaps lead to lower concentrations of delay-effects among this group.

### 4.5. Associations between exposure to delays and modal use

The results show that those whose home-to-workplace OD-pair is associated with a greater concentration of delays by public transport (in the top decile, with a median delay of 4 min or more) (see Table 4) are significantly less likely to travel using public transport for any element of their trip, in comparison to using other motorised modes of transport ( $\mathrm{OR}=0.887(\mathrm{CI}=0.861-0.914)$ ). When the median delay for this ODpair is considered as a continuous variable (in minutes) (see Table 5), for each additional delay the OD-pair is exposed to, all else being equal, there is a lower odds of using public transport (as opposed to other motorised modes). This result indicates that those whose hypothetical trip to work by public transport is associated with delays are significantly less likely to use public transport for any element of the trip and are more likely to use other motorised modes of transport, most commonly the car.

The public transport supply indicator was associated with more than four times the likelihood of travelling using public transport. This result is not surprising, given that a correlation between public transport frequency and use is to be expected. Gender (women), age (those in the age group of $30-44$ ), and (lower) income (those with a household income before taxes of up to 30,000 SEK) were all associated with higher odds of using public transport. These results corroborate previous research findings. Those born in Sweden were associated with a lower likelihood of using public transport, perhaps indicative of the residential concentrations of groups with different backgrounds, albeit perhaps not related to concentrations of income, as the income and background variables were not highly/clearly correlated with one another in these formats.

## 5. Discussion

### 5.1. Findings

In the process of answering the four research questions that were asked in this paper, we found that (1) public transport delays reduce access to jobs by $4-9 \%$ in Scania depending on the travel time threshold that is considered, (2) negative effects caused by public transport delays are more prevalent in rural areas, relatively speaking, (3) people living in cities and in areas with greater proportions of people living in a household with a low economic standard are relatively less exposed to accessibility losses caused by delays, but the absolute numbers are higher, and (4) high exposure to public transport delays is associated with non-use of public transport. Every additional minute of public transport delay is associated with a lower likelihood of using public transport (as opposed to other motorised modes). While these findings are straight-forward and can be summarised relatively easily, there is still a lot of nuance that can be discussed further and expanded on.

When considering the accessibility analysis, identifying where the accessibility losses caused by public transport delays are felt the most, there are multiple ways to consider the spatial distribution of these losses. We looked at the spatial distribution of these effects as they relate to urban areas, but we also looked at the spatial distribution of these effects as they relate to the distribution of households living with a low economic standard. The comparison of these results to the results from the statistical analysis are particularly interesting. The results of the statistical analysis show that lower incomes are related to using public transport, even when public transport delays are considered. This could suggest that captive ridership effects are at play. However, the results from the accessibility analysis show that areas with higher concentrations of people living with a lower economic standard are less exposed to the accessibility impacts of recurring public transport delays. The low income variable in the statistical analysis and the proportion of


Fig. 3. Statistical area categories - Statistics Sweden.
households living with a low economic standard in the accessibility analysis are not exactly the same, but many people will be captured in both groups. Although we do not have the data to paint a complete picture of travel behaviour of people with lower incomes, a comparison of these two results from the accessibility analysis and the statistical analysis shows that people with lower incomes could be more likely to use public transport, because the public transport services in Scania are relatively resilient in areas with higher concentrations of people living with a lower economic standard. In other words, it could be that they use public transport because the services are good, not because they have to, and even if they have to use them, the services and the accessibility they convey are more robust - or less affected by delays - than elsewhere. It should be noted that the results from the statistical analysis only take into account people with jobs, meaning that e.g. those who are unemployed, children, and pensioners are excluded from this part of the analysis while these groups of people are still be included in the accessibility analysis. This difference is worth mentioning since it is unclear how the recurring delays are related to the travel behaviour of these groups of people.

While looking back at previous research about public transport delays and accessibility, we see that our findings are comparable to what was found in São Paulo, Brazil by Arbex and Cunha (2020). Their analysis showed that the travel time unreliability resulted in a $6 \%$ loss in access to jobs. This is interesting considering that São Paulo and Scania are very different study areas. Further research will need to be done to see if 4-9\% losses in accessibility are standard or if this is a coincidence.

There are some noticeable differences between our research and previous research on the topic of public transport delays and reliability.

First, our analysis makes a direct comparison between actual trips from a travel survey and typical public transport travel times. This means that our findings are directly related to observed behaviour, while the findings in other research rely on customer satisfaction surveys (Lunke, 2020; Monsuur, 2022) or stated preference surveys (Deka and Carnegie, 2021). This distinction is important because satisfaction and stated preference do not necessarily directly translate to observed behaviour, and vice versa. Additionally, some research looks at shifts between modes of public transport (Deka and Carnegie, 2021) while the relationship between car and public transport remains unclear. This can be seen in the paper from van Loon et al. (2011). They establish a connection between public transport delays and ticket sales, which we assume is a good indicator of actual use of the system, but it is not clear how these findings relate to modal use in general.

### 5.2. Methodological considerations

The accessibility analysis in this paper uses a cumulative opportunity measure to consider the number of jobs that are accessible within a certain travel time budget. This method is commonly used in accessibility research (Papa and Bertolini, 2015; Lee and Miller, 2022; Singh et al., 2022), but is often criticised for being an overly simplistic representation of accessibility (Geurs and van Wee, 2004). Within this measure, accessibility is binary and opportunities are either accessible within the travel time budget or they are not accessible within the travel time budget. Gravity-based accessibility measures use a decay function to account for diminishing accessibility between origins and destinations as the cost - be it time, distance, or even money - to travel between


Fig. 4. Job accessibility with public transport delays.

Table 2
Average job accessibility in statistical area categories.

|  |  | Travel Time Budget |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | 60 min | $\begin{aligned} & 45 \\ & \text { min } \end{aligned}$ | $\begin{aligned} & 30 \\ & \text { min } \end{aligned}$ |
| Category C <br> Urban areas, central | Accessible Jobs (Scheduled) | 103,307 | 61,369 | 24,763 |
|  | Accessible Jobs (Actual) | 98,902 | 57,404 | 22,605 |
|  | Missed Opportunities (Jobs) | 4405 | 3965 | 2158 |
|  | Percent Accessible <br> (Actual/Scheduled) | 96\% | 94\% | 91\% |
| Category B Urban areas, not central | Accessible Jobs (Scheduled) | 17,058 | 3865 | 476 |
|  | Accessible Jobs (Actual) | 15,451 | 3326 | 433 |
|  | Missed Opportunities (Jobs) | 1607 | 538 | 43 |
|  | Percent Accessible <br> (Actual/Scheduled) | 91\% | 86\% | 91\% |
| Category A Outside of urban areas | Accessible Jobs (Scheduled) | 3670 | 908 | 141 |
|  | Accessible Jobs (Actual) | 3213 | 780 | 100 |
|  | Missed Opportunities (Jobs) | 457 | 127 | 41 |
|  | Percent Accessible <br> (Actual/Scheduled) | 88\% | 86\% | 71\% |

the origins and destinations increases. These measures are often used as more accurate alternatives to cumulative opportunity measures since they are limited by a specific travel time threshold (Geurs and van Wee, 2004). In gravity-based measures, accessibility is not black and white; it is a gradient. Gravity-based measures try to represent accessibility with
more detail, but it is important to keep in mind that that detail does not necessarily reflect reality and the added complexity of gravity-based measures comes with a cost: they are harder to communicate. If it is one's goal to integrate accessibility concepts into planning and policy, then clear, effective communication is key.

Recent publications on accessibility measures explore the relationship between cumulative opportunity measures and gravity-based measures (Santana Palacios and El-Geneidy, 2022; Kapatsila et al., 2023; Klar et al., 2023). Some research indicates that these measures are highly correlated. Kapatsila et al. (2023) compared cumulative opportunity measures and gravity-based measures for public transport accessibility in a number of Canadian cities. They found that cumulative opportunity measures were often highly correlated with gravity-based measures. Specifically, cumulative opportunity measures and gravitybased measures often had correlation coefficients above 0.9 when the travel time threshold was close to the regional mean travel time to work. An earlier study from 2022 showed similar findings (Santana Palacios and El-Geneidy, 2022). This means that, despite the additional detail of gravity-based measures, it is actually possible for comparable accessibility measurements to be produced with a much simpler cumulative opportunities measure.

However, there is not a consensus about the correlation between these two different types of measures. Klar et al. (2023) performed a similar analysis to the one that was carried out by Santana Palacios and El-Geneidy, 2022, but found that cumulative opportunity measures and gravity-based measures often produced very different results and the correlation coefficients between the two measures were usually weak to moderate (below 0.7). There are two important differences between the analysis carried out by Klar et al. (2023) and the analyses carried out by Kapatsila et al. (2023) and Santana Palacios and El-Geneidy (2022).


Fig. 5. Missed opportunities due to delays (Weighted).

Table 3
Average job accessibility for households living in a household with a low economic standard.

|  |  | Travel Time Budget |  |  |
| :---: | :---: | :---: | :---: | :---: |
|  |  | $\begin{aligned} & 60 \\ & \min \end{aligned}$ | $\begin{aligned} & 45 \\ & \text { min } \end{aligned}$ | $\begin{aligned} & 30 \\ & \min \end{aligned}$ |
| Quintile 1 <br> Lowest proportion of low economic standard population | Missed Opportunities (Jobs) | 3865 | 2335 | 496 |
|  | Percent Accessible <br> (Actual/Scheduled) | 92\% | 88\% | 89\% |
| Quintile 2 | Missed Opportunities (Jobs) | 2027 | 1421 | 651 |
|  | Percent Accessible <br> (Actual/Scheduled) | 95\% | 94\% | 92\% |
| Quintile 3 | Missed Opportunities (Jobs) | 4219 | 3043 | 1630 |
|  | Percent Accessible <br> (Actual/Scheduled) | 95\% | 93\% | 89\% |
| Quintile 4 | Missed Opportunities (Jobs) | 2844 | 2531 | 1255 |
|  | Percent Accessible <br> (Actual/Scheduled) | 96\% | 94\% | 92\% |
| Quintile 5 <br> Highest proportion of low economic standard population | Missed Opportunities (Jobs) | 3791 | 4039 | 2691 |
|  | Percent Accessible <br> (Actual/Scheduled) | 97\% | 94\% | 92\% |

First, Kapatsila et al. (2023) and Santana Palacios and El-Geneidy, 2022 both look at accessibility to jobs, while Klar et al. (2023) look at multiple types of opportunity data, not just jobs. Second, Klar et al. (2023) consider three travel time thresholds (30, 60, and 90 min ) while Kapatsila et al. (2023) and Santana Palacios and El-Geneidy (2022) look

Table 4
Binary logistic model of modal use with delay exposure as categorical variable likelihood of using public transport (for any element of the trip) compared to using other motorised modes and not public transport.

| Independent variables included in the final <br> model | $p$-value | Odds Ratio <br> (95\% Confidence <br> Interval) |
| :--- | :--- | :--- |
| Potential exposure to delays by public <br> transport indicator <br> positive median delay in minutes <br> top decile (4 min or more) $=1$, lower $=0$ <br> Public transport supply indicator <br> hourly departures by public transport in the <br> local vicinity <br> top decile $=1$, lower $=0$ | $<0.001$ | $0.887(0.861-0.914)$ |
| Gender |  |  |
| women $=1$, men $=0$ | $<0.001$ | $4.278(4.120-4.441)$ |
| Age <br> aged $30-44=1$, other $=0$ <br> Income <br> lower $=1$, higher and other/not reported $=0$ | $<0.001$ | $1.796(1.758-1.833)$ |
| Background <br> born in Sweden $=1$, born outside of Sweden <br> $=0$ | $<0.001$ | $0.523(0.509-0.537)$ |
| Constant | $<0.001$ | 0.472 |

Cox \& Snell R Square $=0.069$ Nagelkerke R Square $=0.097$. Percentage correctly classified: $71.5 \%$ (cut-off $=0.5$ ).
at many more travel time thresholds, spaced out in smaller intervals. It is possible that some variation in these results can be attributed to the characteristics of the study areas, butthese studies look exclusively at Canadian cities, meaning that urban areas with very different structures,

Table 5
Binary logistic model of modal use with delay exposure as continuous variablelikelihood of using public transport (for any element of the trip) compared to using other motorised modes and not public transport.

| Independent variables included in the final model | p-value | Odds Ratio <br> (95\% Confidence <br> Interval) |
| :---: | :---: | :---: |
| Potential exposure to delays by public transport indicator positive median delay in minutes | <0.001 | 0.969 (0.965-0.974) |
| Public transport supply indicator <br> hourly departures by public transport in the local vicinity top decile $=1$, lower $=0$ | <0.001 | 4.173 (4.011-4.341) |
| Gender women $=1$, men $=0$ | <0.001 | 1.770 (1.731-1.809) |
| Age aged $30-44=1$, other $=0$ | <0.001 | 1.129 (1.103-1.155) |
| Income lower $=1$, higher and other/not reported $=0$ | $<0.001$ | 1.355 (1.310-1.401) |
| ```Background born in Sweden = 1, born outside of Sweden \(=0\)``` | <0.001 | 0.523 (0.508-0.538) |
| Constant | $<0.001$ | 0.513 |

Cox \& Snell R Square $=0.069$ Nagelkerke R Square $=0.097$. Percentage correctly classified: $70.8 \%$ (cut-off $=0.5$ ).
such as other North American and European cities, are not being compared to one another. However, despite the differences in methods and results, Klar et al. (2023) emphasise the importance of the role that travel time thresholds can play in cumulative opportunity accessibility measures and recommend testing multiple travel-time thresholds when evaluating accessibility.

Public transport delays are not usually included in public transportbased travel time estimates and accessibility modelling. At the same time, the fact that a considerable proportion of private vehiclekilometres exceed permitted speed limits is not accounted for in carbased travel time estimates (Swedish Transport Administration, 2019). Recurring road congestion is often accounted for in the car travel time estimates produced by route planners meaning that these estimates are likely to be more accurate (true to reality) and allow travellers to adjust their expectations and plans accordingly. This is not the case for public transport trip/route planning. This implies that the car is more likely to actually complete the trip during a tighter timeframe than was estimated by the route planner (and the individual carrying out the trip) since the estimated travel time typically does not take speeding into account and includes extra minutes to account for typical congestion, which decreases the chance that the actual travel time will exceed the estimated travel time. This is likely to have a positive effect on trip satisfaction by car. This in turn indicates that travel time ratios produced by accessibility models may be misleading. The exclusion of public transport delays and excessive speeds by private motorised vehicles on the one hand, and the inclusion of road congestion on the other, is all to the benefit of car travel. This, in turn, suggests that we systematically underestimate the accessibility conveyed by car-based travel and overestimate the accessibility conveyed by the public transport system.

### 5.3. Limitations

The recurring delay measures that were used in this paper were based on morning peak travel times in a single month over two years. This time window was used for three reasons. First, we wanted the public transport travel times that were estimated using the actual arrival and departure times to correspond with the time period that was used for data collection in the regional travel survey. We chose October since the travel survey was conducted in autumn. Second, the travel survey specifically looked at people's commute from home to work. Therefore, we kept the focus on the morning commute hours instead of looking at an
entire day. Third, the process of calculating parallel sets of public transport travel times between thousands of origins and destinations over multiple years is computationally intensive and requires lots of time. Because of this, it was not reasonable to look at more years of data. Future research that looks at the role of recurring delays on public transport accessibility and travel behaviour might want to consider looking at more years of data and more hours throughout the day in order to see how these types of delays affect accessibility for different types of trips.

There are additional limitations relating to the actual vehicle arrival and departure times provided by the public transport provider. These data are typically derived form GPS traces and are not immune from error. In particular, it is possible that some trips simply might not be recorded. However, had significant errors been present, routing with the synthesised GTFS data would not have been possible or would have shown more severe delays than what was observed.

This study uses a binary logistic regression model to assess how public transport delays are associated with the likelihood that public transport will be used. Typically, a mode-choice analysis might use a discrete choice model since mode-choice is not binary and one might have the opportunity to choose between all available transportation modes. While mode choice is complicated and involves many competing attributes of multiple transportation modes, we employed a binary logistic regression model to keep the focus on how a specific variable (public transport delays) is associated with the likelihood that public transport will be used. A more robust model might consider car travel times or more detailed attributes of other modes. For example, as described in the previous section, discrepancies in how route planners do or do not take expected delays into account may affect how people perceive or react to delays in their trips, not just for public transport, but also for other modes. This is not being captured in the existing model, and limits the conclusions we can draw from the results.

### 5.4. Recommendations for future research

Future research on the topic of public transport delays, accessibility, and travel behaviour may want to consider expanding the concept of recurring delays that was presented in this paper. This might mean looking at longer time periods or different observation periods, such as off-peak times or a mix of peak and off-peak times. Additionally, the quality of public transport services varies greatly from place to place and different results could be seen in different study areas.

Further research on the topic of delay measures could also compare the measure used and proposed in this research to other delay measures that have been used in other papers, such as the 80th minus the 50th percentile of travel time (van Loon et al., 2011) or the standard deviation of schedule deviation (Chakrabarti, 2015). While comparisons of such measures could be useful and interesting, this is not the main focus of the current study.

## 6. Conclusion

This paper set out to use a two-pronged approach to explore the role of recurring public transport delays in accessibility and travel behaviour in Scania, Sweden. We examined these relationships with a cumulative opportunity accessibility analysis and a binary logistic regression model. Not only does our research show that recurring delays can play an important role in both accessibility and travel behaviour, but we also argue that recurring delay measures can be an important addition to research about public transport reliability.

At the start of this paper we presented four research questions and through an accessibility analysis and a statistical analysis we produced the following findings for these research questions:

RQ1. How do public transport delays affect the number of accessible jobs?

Public transport delays reduce access to jobs by $4-9 \%$ in Scania
depending on the travel time threshold that is considered.
RQ2. How are these relative changes in accessibility distributed?
Negative effects caused by public transport delays are more prevalent in rural areas, relatively speaking.

RQ3. Where are the accessibility losses due to delays concentrated?
People living in cities and in areas with greater proportions of people living in a household with a low economic standard are relatively less exposed to accessibility losses caused by delays, but the absolute numbers are higher.

RQ4. Are those that are exposed to more public transport delays less likely to use public transport?

High exposure to public transport delays is associated with non-use of public transport among commuter OD pairs.

The implications of this research are twofold. First, systemic issues, even minor ones, can not only have impacts on individual mode-choice, but can also have impacts on the effectiveness of a transportation system at providing access to goods and services within a region. Second, this research shows that, when combined with detailed travel time estimates, travel survey data can be used to derive revealed preferences for different mobility options under different conditions. This work is significant because recurring delay measures are employed and demonstrated to have a relationship with both estimated accessibility and travel behaviour.

## Data availability

Data will be made available on request.

## Acknowledgements

This study was funded by K2 - The Swedish Knowledge Centre for Public Transport (grant agreement number 20200012). Open access funding provided by Lund University. We are grateful to Skånetrafiken for sharing the data used in this study.

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[^1]:    ${ }^{1}$ These weights were calculated by those responsible for the administration of the dataset.
    ${ }^{2}$ This was not reported by respondents but was drawn from the population register.
    ${ }^{3}$ Respondents were asked to report the combined monthly income for all persons in their household before tax. Respondents were asked to include pensions and study loans, but not child support and other similar forms of social welfare payments (such as housing supports).
    ${ }^{4}$ This was the equivalent of 3309 USD on 4 October 2018 (xe.com).

[^2]:    ${ }^{5}$ An 'urban area' ('tätort' in Swedish) is defined by Statistics Sweden as a coherently built-up urban area with at least 200 inhabitants. See Statistics Sweden (2022) for more information. Statistics Sweden determines the geographical boundaries and the statistics per urban area. Each municipality has a 'central' urban area in which the administrative and other services are concentrated. Most municipalities also have other 'not central' urban areas, i.e. towns and villages that are not the administrative centre of the municipality.
    ${ }^{6}$ A low economic standard relates to people living in households with an economic standard lower than $60 \%$ of the median value in the population as a whole. The economic standard for a household (and for people in the household) is measured by adjusting the household's disposable income according to the household's composition (Statistics Sweden, 2017).

