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How built environment factors shape demand for demand-responsive transport services: spatiotemporal patterns from a German case study

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A B S T R A C T

Demand-responsive transport (DRT) services are becoming increasingly important as a flexible supplement to fixed-route public transportation. However, many DRT services face challenges due to high operating costs. Spatially and temporally detailed insights into the influence of the built environment on DRT demand can provide a valuable basis for designing and operating DRT services cost-effectively. This study examines the impact of built environment characteristics on DRT demand using the example of a DRT service in southern Hamburg, Germany. We utilize DRT trip data from 2024 and spatial regression models at the level of small-scale grid cells. In addition to overall demand, we investigate five selected time-of-week periods to identify temporal differences in the significance of built environment factors. The results indicate that rail stations, hospitals, and population hotspots are key drivers of DRT demand across all periods considered. In contrast, factors such as dining establishments, cultural institutions, doctors' offices, schools, and concentrations of workplaces were only significant during specific time periods. Grocery and retail stores negatively affected DRT demand outside their typical opening hours and had a strong impact not only on their own locations but also on neighboring areas. Access times to fixed-route public transportation increased DRT demand, but only during periods with comparatively weak public transit services, highlighting the role of DRT in addressing gaps in conventional public transportation. Based on these findings, we derive practical implications for operating DRT services in a more cost-effective and user-friendly manner.

1. Introduction

1.1. Background

Demand-responsive transport (DRT), also known as on-demand or flexible public transport, is a dynamic form of collective transport in which routes, stops, and departure times are designed based on actual user demand (Alonso-González et al., 2018; Shibayama & Emberger, 2020). In contrast to conventional, fixed-route public transportation, which operates in a largely static manner, DRT allows for flexible and adaptive service. This is usually accomplished through booking via app or telephone, with algorithms coordinating trips in real time. The vehicles, primarily minibuses or vans, serve predefined (and often virtual) stops or offer door-to-door connections within specific service areas. Different DRT systems vary in terms of degree of flexibility, pooling capability, and integration with conventional public transportation (Alonso-González et al., 2018; Baier et al., 2024).

DRT services are not a recent phenomenon. They have been employed in Europe and North America since the 1960s but had remained a niche offering in these regions for decades (Currie & Fournier, 2020; Davison et al., 2014; Nutley, 1988). However, in the context of evolving mobility needs, growing pressure for sustainable transportation planning, and the advent of modern information and communication technologies, DRT has gained prominence since the 2010s as a complement to conventional public transport (Coutinho et al., 2020; Currie & Fournier 2020; Shibayama & Emberger, 2020). In areas where fixed-route public transportation is of poor quality due to low demand, particularly in peripheral, suburban, or rural regions, DRT is often regarded as a potential solution to enhance user satisfaction and cost effectiveness of public transit services (Brake et al., 2007; Ryley et al., 2014; Schasché et al., 2022).

Research has demonstrated that implementing DRT in areas or periods with inadequate fixed-route public transportation results in significant improvements in accessibility, reduced travel times, and increased user comfort (e.g., Alonso-González et al., 2018; Haglund et al., 2019; Mortazavi et al., 2024). This is particularly beneficial for

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demographic groups that are often dependent on public transportation and susceptible to social exclusion, including the elderly, individuals with low incomes, those without personal vehicles, and persons with disabilities (Burlando et al., 2025; Drake & Watkins, 2024; Kuehnel et al., 2025; Liezenga et al., 2024; Mayaud, 2025; Nelson & Phonphitakchai, 2012; Wang et al., 2014; Wang et al., 2015; Wang & Shen, 2024). Therefore, DRT appears to engender not only an increase in overall mobility but also a strengthening of social inclusion by opening up new mobility options for disadvantaged populations.

However, the expectation that DRT will make public transit services more economical to operate has yet to be substantiated by empirical evidence. Studies from Amsterdam, Netherlands (Coutinho et al., 2020), Canberra, Australia (Mortazavi et al., 2024), and Porto, Portugal (Melo et al., 2024) have consistently concluded that replacing underutilized bus routes with DRT leads to greater cost efficiency and, due to a reduction in vehicle kilometers, to lower greenhouse gas emissions. Nevertheless, DRT services often prove financially unsustainable for long-term deployment (Ryley et al., 2014). Consequently, high costs are the primary reason why, since the 2010s, approximately half of all newly introduced DRT services in Europe, North America, and Australasia, especially the more extensive and complex ones, have been discontinued after only a few years of operation (Currie & Fournier, 2020).

The failure of many modern DRT services due to cost issues highlights the importance of aligning DRT operators' limited resources with local needs. Transportation research can contribute to this by providing spatially and temporally differentiated insights into the determinants of DRT demand. In this context, it is particularly relevant to study the impact of built environment factors, such as urban density, land use, the distribution of various points of interest, and the accessibility of fixed-route public transit services. These spatial factors have a significant impact on travel demand and mobility behavior, and can therefore be expected to influence the acceptance and use of DRT services as well. Moreover, spatial data is typically more readily available and easier to interpret for planners, policymakers, and DRT operators than, for example, sociodemographic characteristics or individual attitudes, which usually require costly and time-consuming surveys. Insights into the impact of built environment characteristics on DRT demand can thus provide a valuable basis for planning and managing a cost-effective and socially acceptable DRT operation.

1.2. *Previous research on spatial determinants of DRT demand*

In parallel with their growing importance in transportation planning, DRT services have received increasing attention in transportation research since the early 2010s (Schasché et al., 2022). Numerous previous publications have examined factors that encourage or discourage DRT usage, primarily focusing on the personal characteristics and attitudes of (potential) users of hypothetical or existing DRT systems (e.g., Burghard & Scherrer, 2022; Capodici et al., 2024; Drake & Watkins, 2024; Geržinič et al., 2023; König & Grippenkoven, 2020; Nelson & Phonphitakchai, 2012; Rossetti et al., 2023; Schneider et al., 2025; Vij et al., 2020; Wang & Shen, 2024). In contrast, studies on the relationship between the built environment and DRT demand are relatively rare. These studies also provide partially inconsistent results, which can likely be attributed to their diverse geographical and operational contexts.

For instance, Imhof & Blättler (2023) examined a DRT service in two rural Swiss communities and identified rail stations, restaurants, healthcare facilities, and general population hotspots as significant drivers of DRT demand. Similarly, Thao et al. (2023) found in their study of a DRT service in a *peri*-urban area in Switzerland that residential areas and rail stations, in addition to commercial areas and retirement homes, were the most important pickup and drop-off locations for DRT trips. The importance of rail stations for DRT demand has been observed on multiple occasions, which is not unexpected, as DRT systems are frequently designed with the explicit purpose of serving as a first/last mile supplement to higher-capacity public transportation. In line with this, Ryley et al. (2014) demonstrated in their analysis of potential market niches for DRT services in the United Kingdom that DRT services designed specifically to provide access to rail stations are among the few types that can achieve financial viability.

However, according to current research, the role of rail stations as origins and destinations of DRT trips appears to differ between urban and less densely populated areas. For instance, in their simulation of a DRT service in the greater Munich area of Germany, Zubair et al. (2025) found that suburban residents would primarily use DRT for trips to and from larger public transportation hubs, whereas urban residents would use DRT primarily for intra-urban travel. These findings are consistent with those of Zuniga-Garcia et al. (2022). By examining a DRT service in Austin (Texas), United States, they concluded that DRT designed purely as a first/last mile solution to fixed-route public transportation is not appealing in areas with high population *and* workplace densities, presumably due to the high proportion of intra-zonal trips in such areas.

Other studies have identified areas with a high density of jobs and other economic activity as centers of DRT demand as well. According to Ghimire & Bardaka (2025a), demand for a DRT service in Wilson (North Carolina), United States, increased with the number of health-related jobs, business-related jobs, and commercial, administrative, leisure, and recreational points of interest at the neighborhood level. Research by Liezenga et al. (2024) on DRT services in the suburbs of Minneapolis–Saint Paul, United States, revealed that DRT trips typically began in residential or business areas, with nearly every second trip connecting these land uses.

However, a study by Pan & Shaheen (2025) yielded different results. Their analysis of 32 DRT services in suburban areas across various cities in the United States found that spatial factors, such as workplace density and points of interest, contributed only modestly to explaining DRT demand. Factors related to the DRT services themselves were more important, such as operating hours and the size of the service areas. In their analysis of five DRT systems in the United States, Ghimire & Bardaka (2025b) confirmed the importance of system design attributes in explaining DRT usage; yet, they also identified spatial factors, such as proximity to population hotspots and commercial and health-related land uses, as important determinants. Wang et al. (2023) used the example of a DRT system in Dalian, China, to argue that DRT demand is *primarily* determined by characteristics of the built environment, such as population and workplace densities or limited parking options. The authors also emphasize the importance of considering that the built environment has different impacts on DRT and conventional public transportation.

This distinction is particularly evident in rural and suburban regions. Due to their low population density, these areas often present particular challenges for the provision of efficient fixed-route public transportation. Conversely, DRT services tend to experience comparatively high demand in such areas, according to previous research (Capodici et al., 2024; Dytckov et al., 2022; Pan & Shaheen, 2025; Tejero-Beteta et al., 2024; Wang et al., 2014). This phenomenon is further substantiated by the findings of Jain et al. (2017), who observed an imbalanced spatial distribution of susceptibility to DRT and conventional public transportation in the greater Melbourne area of Australia. The authors noted that DRT susceptibility was more pronounced in peripheral regions of the area; however, areas of increased DRT susceptibility were also identified in more central parts of the city, such as those adjacent to the Central Business District. Other studies have corroborated that DRT can be an attractive mobility option in urban areas as well, especially during times or in areas with limited availability of fixed-route public transportation. Research in major cities such as Nijmegen, Netherlands (Alonso-González et al., 2018) or Helsinki, Finland (Haglund et al., 2019) revealed a high demand for DRT services, particularly for trips that would have taken significantly longer with conventional public transportation, such as tangential or orbital trips outside the city center.

Overall, existing research suggests that DRT demand is shaped by a complex interaction between built environment characteristics and service design attributes, with considerable variation across geographical and operational contexts. While rail stations, residential areas, and commercial or healthcare-related land uses frequently emerge as important generators of DRT trips, their relative importance differs between urban, suburban, and rural settings. In less densely populated areas, DRT often functions effectively as a first/last mile connection to fixed-route public transportation, whereas in urban contexts it may serve a broader range of intra-urban mobility needs, particularly where conventional public transportation is less efficient. However, previous studies have produced partly inconsistent findings regarding the spatial determinants and usage patterns of DRT services, indicating that these relationships remain insufficiently understood. Moreover, temporal variations in the influence of built environment characteristics on DRT demand have received only limited attention in the existing literature. Consequently, further research focusing explicitly on the spatiotemporal patterns of DRT demand is needed to improve our understanding of how demand drivers vary across both space and time.

1.3. Aim and relevance of this study

The failure of many previous DRT systems highlights the importance of being able to realistically estimate demand for such services prior to their implementation (Ronald et al., 2015). In the absence of more suitable data, simulations of DRT systems often rely on mobile phone network data (Franco et al., 2020; Mahfouz et al., 2025), conventional public transit usage data (Kim et al., 2023), taxi trip data (Bischoff et al., 2018), or general mobility data from travel surveys (Höing et al., 2025) to estimate potential DRT demand. Moreover, the delineation of DRT service areas is frequently driven by operators' interests in maximizing operational efficiency. Successful DRT services, however, must strike a balance between the objectives of operators and the needs of actual and potential users (Mahfouz et al., 2026). To improve simulations of DRT systems, empirical evidence from existing services is particularly valuable. Case studies, in particular, enable researchers to investigate the real-world dynamics of DRT demand in natural settings and thereby contribute to a deeper understanding of factors that promote or inhibit DRT usage.

In light of this, the present paper examines the influence of various characteristics of the built environment on DRT demand using the example of an existing DRT service in the southern part of Hamburg, Germany's second-largest city. The focus on built environment characteristics can be justified for two reasons. First, previous research has produced partly inconclusive results regarding their influence on DRT demand and has largely neglected temporal variations in the importance of different built environment factors. Second, analyses of the relationship between the built environment and DRT demand are likely to be transferable across different geographical and operational contexts. In contrast to surveys of actual or potential DRT users, built environment data can be obtained and applied relatively easily and cost-effectively for demand estimation purposes. This is particularly true when using open geospatial data, the availability of which continues to increase through initiatives such as OpenStreetMap.

In our study, we operationalize DRT demand based on pickup and drop-off locations of DRT trips made in southern Hamburg throughout the year 2024. Our investigation utilizes spatial regression analyses at the level of small-scale grid cells, with each cell measuring one hectare (i.e., 100 × 100 m). Previous studies on the determinants of DRT demand have frequently relied on aggregated data at larger spatial scales, such as neighborhoods or statistical zones (e.g., Ghimire & Bardaka, 2025b; Pan & Shaheen, 2025; Zwick & Axhausen, 2022). Although valuable insights can also be gained at these coarser levels of spatial resolution, more granular analyses allow for more precise and reliable conclusions regarding the spatial relationships between the built environment and DRT demand and therefore provide a stronger basis for operational and planning decisions.

In addition to analyzing total DRT demand throughout the year 2024, we examine DRT demand during specific time-of-week periods (e.g., during peak hours on weekdays or during the evening and night hours on Fridays and Saturdays) to identify temporal changes in the significance of built environment factors. For the evaluation of existing and potential DRT systems, it is important not only to understand how the built environment influences DRT demand in general, but also whether and to what extent these effects vary over time. Particularly in larger DRT systems, such insights can support a more efficient allocation of resources by enabling operators to concentrate vehicles in areas of high demand during specific periods or to implement service area boundaries that vary according to temporal demand patterns.

In summary, the objective of our study is to address the following two research questions:

(1) What impact do different characteristics of the built environment have on DRT demand?
(2) How does the impact of different characteristics of the built environment on DRT demand vary between different periods within a typical week?

The remainder of this paper is structured as follows: Section 2 details the study area and the DRT service operating there, and explains the procedure for preparing and analyzing the data. The key findings are then presented in Section 3 and interpreted and discussed in Section 4 within the context of previous research.

2. Methods and data

2.1. Study context

This study utilizes a DRT service in Harburg, a borough in southern Hamburg, Germany, as a case study. Until 1938, Harburg was an independent city; today, it is an important sub-center within Hamburg. The borough is composed both of an urban core with a high concentration of population and economic, social, and cultural activities, as well as less densely populated residential areas in the periphery. Consequently, the availability of fixed-route public transportation decreases significantly toward the periphery, with most services concentrated on radial bus routes. The borough's urban core is well-connected to the rest of Hamburg and beyond by three commuter rail stations and a mainline rail station.

To support conventional public transportation in the borough of Harburg, *vhh.mobility* — a major public transportation operator in the greater Hamburg area — launched the DRT service *hvv hop* in January 2023. In 2024, the year under investigation in this study, the DRT service operated up to 20 electric-powered vans simultaneously. Each van had a maximum capacity of six passengers, and most of the vans were wheelchair-accessible. Bookings could only be made via app. The service was available on a 24/7 basis. A conventional public transit ticket and a so-called "comfort surcharge" of €2 per trip were required for the ride. Weekly and monthly tickets for the surcharge were available at flat rates for frequent users. The service was complimentary for individuals with documented severe disabilities.

The DRT service examined was a hybrid between a door-to-door service and a first/last mile solution. Users could specify any two points within the service area as their desired pickup and drop-off location in the app; yet, since the DRT service was legally required to differentiate from taxicabs, the DRT operator had to relocate one of these locations to a nearby bus stop or a virtual pickup/drop-off point. However, given that the virtual pickup/drop-off points were mostly situated at intervals of only 200–300 m from each other and from existing bus stops, the distances to and from the pickup and drop-off locations were generally short. The operator pooled trip requests with similar routes, which meant that desired destinations were not always approached directly and that other passengers could join or leave the vehicle during the trip.

2.2. Preparation of the dependent variables

For our analyses, we operationalize DRT demand based on the pickup and drop-off locations of DRT trips undertaken throughout the year 2024. These trips represent the revealed preferences of DRT users, allowing for reliable conclusions regarding DRT demand. In 2024, the DRT service under investigation recorded a total of 177,556 trips across the entire service area, with demand showing substantial variation over the course of the day and week (Fig. 1).

DRT trip data was provided to us for this study by the DRT operator. Our analyses refer to the original pickup and drop-off locations requested by users when booking, *before* the operator reassigned one of these locations to a bus stop or a virtual pickup/drop-off point. As this data could be used to identify individuals, we aggregated it at the level of one-hectare grid cells to protect user privacy. The grid cell system was provided by the German Federal Agency for Cartography and Geodesy (Bundesamt für Kartographie und Geodäsie, 2025).

When defining the service area, the DRT operator aligned the outer boundaries partly with the city limits and partly with major physical barriers, such as a highway in the west and the Elbe River in the north. Consequently, the service area encompassed large areas that were inaccessible to the DRT service, such as bodies of water, farmland, and forest areas, which were not pertinent to our analyses. We therefore limited our study area to the built-up parts of the service area that could be reached via public roads. This approach resulted in the difference between the service area and the study area illustrated in Fig. 2. However, the number of DRT pickups or drop-offs in each cell was not a determining factor in the delineation of our study area. Accordingly, our analyses also consider grid cells that exhibited no DRT demand in 2024, despite being located in built-up areas.

In addition to examining DRT demand for the entire year of 2024, our study explores DRT demand in five selected *time-of-week periods* (TOWPs) in order to investigate temporal changes in the influence of built environment characteristics on DRT demand. Specifically, we will examine the following TOWPs, with the numbers in parentheses indicating the number of DRT trips initiated in each TOWP in 2024:

- TOWP 1: Monday–Friday, 6:00 AM–9:00 AM (weekday morning period; 19,350 trips)
- TOWP 2: Monday–Friday, 3:00 PM–6:00 PM (weekday afternoon period; 23,247 trips)
- TOWP 3: Friday–Saturday, 8:00 PM–12:00 AM (weekend nighttime period; 11,044 trips)
- TOWP 4: Saturday, 3:00 PM–6:00 PM (Saturday afternoon period; 3343 trips)
- TOWP 5: Sunday, 5:00 PM–8:00 PM (Sunday evening period; 3152 trips)

We selected these TOWPs because they generally correspond to the periods of highest DRT demand over the course of the week (Fig. 1). Furthermore, they vary in terms of the expected predominant mobility motives of travelers (e.g., commuting to work or school, nightlife mobility, weekend activities) and in terms of the frequency of fixed-route public transit services.

In both the analysis of total DRT demand in 2024 and the analysis of demand in the TOWPs, we consider the pickup and drop-off locations of DRT trips separately. When examining all DRT trips recorded in 2024, there was a remarkably strong positive correlation between the number of pickups and drop-offs at the grid cell level ($r = 0.98$; $p < 0.001$), suggesting a consistent spatial distribution of DRT trip origins and destinations. However, this correlation was much weaker in the individual TOWPs. In TOWP 1 (weekday morning period), for instance, the correlation between the number of DRT pickups and drop-offs was only moderate ($r = 0.35$; $p < 0.001$), emphasizing the need to examine DRT trip origins and destinations independently.

The distribution of DRT pickups and drop-offs across the grid cells was highly skewed. While many cells exhibited only single- or double-digit numbers of pickups and drop-offs in 2024, and in some cases no DRT demand at all, a few cells accounted for well over 1000 pickups and drop-offs each (Fig. 2). We therefore transformed the number of DRT pickups and drop-offs using the natural logarithm. In doing so, we added the smallest positive value in the dataset as a constant to each cell value (i.e., $\ln[y + 1]$) to allow for the inclusion of cells with zero values in the analyses.

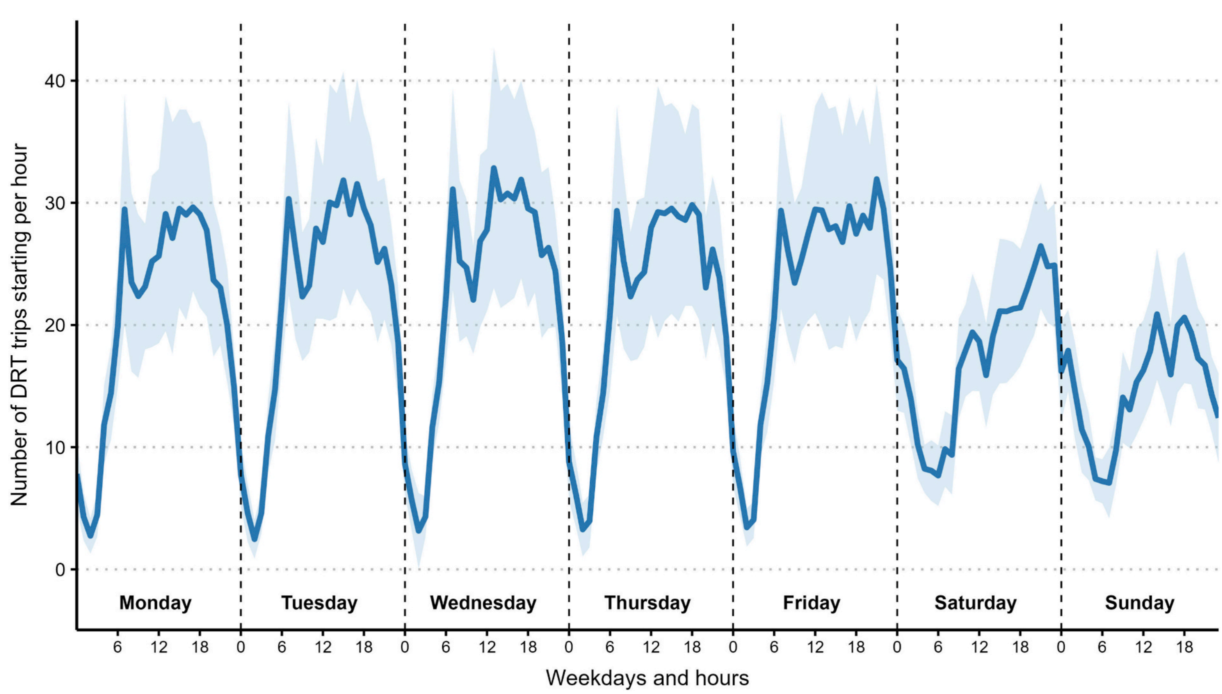

Fig. 1. Temporal profile of DRT demand over the course of the week. The solid line shows the mean number of DRT trips starting each hour; the shaded areas show the respective standard deviations. The figure refers to all DRT trips made in the study area in the year 2024.

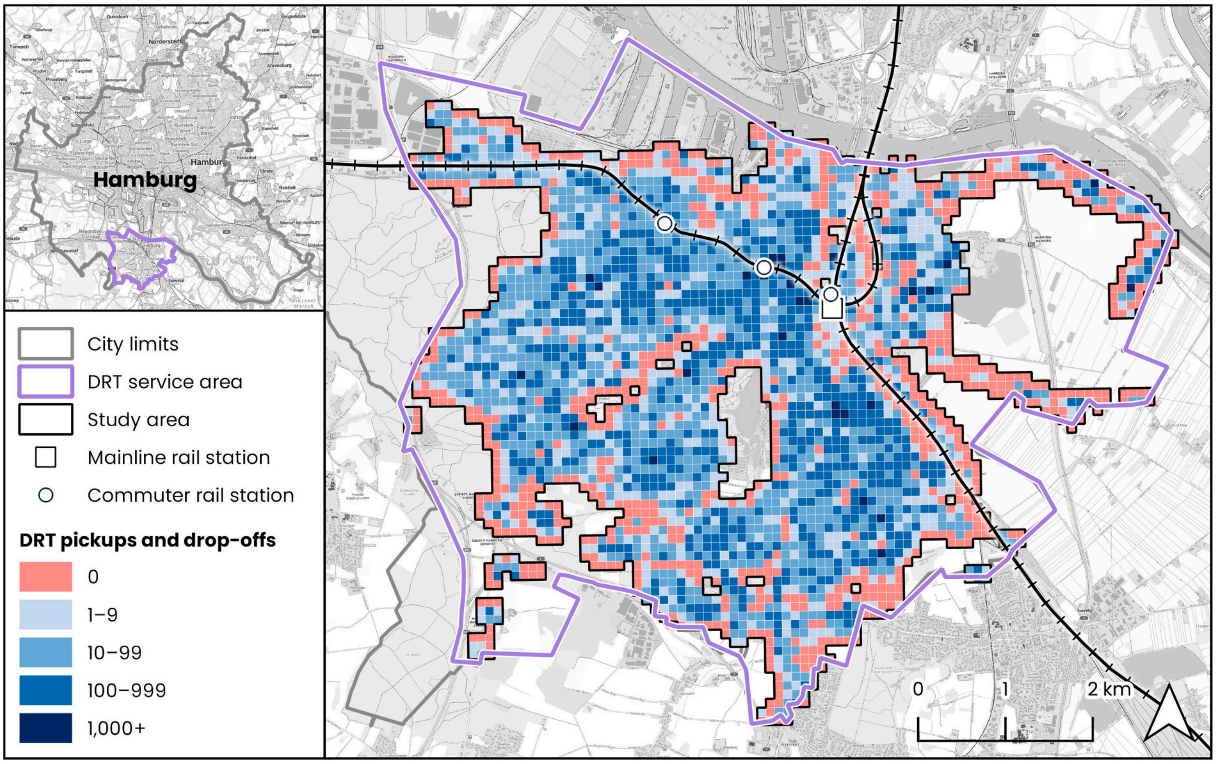

Fig. 2. Overview of the study area and the spatial distribution of DRT demand. The figure shows the total number of DRT pickups and drop-offs in each grid cell in the year 2024. The basemap was provided by the German Federal Agency for Cartography and Geodesy.

2.3. Preparation of the independent variables

Table 1 provides an overview of the variables used in this study to explain DRT demand. With the exception of the number of workplaces, which was provided to us by the City of Hamburg, we exclusively used publicly available data, such as from the 2022 Census (Statistisches Bundesamt, 2025) and from OpenStreetMap (OpenStreetMap contributors, 2025), when compiling the independent variables. As with the DRT trip data, we also aggregated the data for the independent variables at the grid cell level.

The selection of the independent variables combined both confirmatory and exploratory considerations. On the one hand, we included spatial factors that have previously been identified as determinants of DRT demand, such as retail stores, healthcare facilities, and the general distribution of residents and workplaces. On the other hand, we sought to incorporate characteristics of the built environment that have received comparatively little attention in the existing literature but could plausibly influence DRT demand. In our study, this particularly applies to education-related points of interest, especially schools, as the DRT service under investigation could be used independently by minors due to the availability of prepaid travel cards.

We grouped the points of interest (POI) contained in the OpenStreetMap data into broader categories in order to keep the regression models as parsimonious as possible. As OpenStreetMap data can be of varying quality, we carefully reviewed, corrected, and supplemented these data using other map services (e.g., Google Maps) and our own knowledge of the study area.

The category *grocery store* comprises POIs associated with the provision of daily necessities, including supermarkets, convenience stores, bakeries, and drugstores. The category *retail store* encompasses a broad range of specialty retail establishments, such as clothing stores, electronics retailers, department stores, and various local shops. *Cultural institutions* include museums, theaters, cinemas, clubs, and other music venues. The category *dining establishment* covers restaurants as well as pubs, bars, cafés, and fast-food outlets. Other POI categories, such as *school* and *doctor's office*, could largely be adopted directly from the OpenStreetMap data without further aggregation.

The study area also includes several larger facilities (e.g., a university with two campuses, two hospitals, a mainline rail station, and three commuter rail stations) that could not be reasonably assigned to single cells. At our granular level of analysis, we therefore considered such facilities as *areas of interest* (AOI) and distributed them across multiple cells. However, only cells containing access points or entrances to these facilities were classified as belonging to the corresponding AOI.

To facilitate interpretation, the numbers of residents and workplaces were included in the analyses in units of ten, as individual residents or workplaces were expected to have a negligible impact on DRT demand. To examine the extent to which DRT demand is influenced by the service quality of fixed-route public transportation, we additionally included the independent variable *transit access time*. This variable was modeled based on the walking time from the centroid of each grid cell to the nearest public transit stop and the average headway of fixed-route public transit services departing from that stop. To account for temporal variations in service frequency, separate transit access time values were calculated for each time-of-week period.

In addition to the independent variables whose (potential) influence on DRT demand we were interested in ("substantive variables", Table 1), our analyses also include the locations of bus stops and bus depots as control variables. The importance of considering bus stop locations stems from the fact that the DRT pickup or drop-off locations requested by users were relocated by the DRT operator to a nearby bus stop or virtual pickup/drop-off point (see **Section 2.1**). While our analyses are based on the original data on requested pickup and drop-off locations prior to this reassignment, preliminary data analysis suggested that certain DRT users set their requested pickup or drop-off location at a bus stop themselves, thereby ensuring an address-specific service at the other end of the trip. Consequently, a significant concentration of DRT demand was observed at bus stops, necessitating the incorporation of

Table 1
Overview of the variables used in the regression models.

Variables	Levels of measurement	Data sources
Dependent variables		
Number of DRT pickups	Count, log-transformed	DRT operator (data not publicly available)
Number of DRT drop-offs	Count, log-transformed	DRT operator (data not publicly available)
Substantive variables		
Number of residents (×10)	Count, treated as metric	2022 census
Number of workplaces (×10)	Count, treated as metric	City of Hamburg (data not publicly available)
Grocery store (POI)	Binary (1 = present)	OpenStreetMap contributors
Retail store (POI)	Binary (1 = present)	OpenStreetMap contributors
Cultural institution (POI)	Binary (1 = present)	OpenStreetMap contributors
Dining establishment (POI)	Binary (1 = present)	OpenStreetMap contributors
School (POI)	Binary (1 = present)	OpenStreetMap contributors
University (AOI)	Binary (1 = present)	Mapped by the authors
Doctor's office (POI)	Binary (1 = present)	OpenStreetMap contributors
Hospital (AOI)	Binary (1 = present)	Mapped by the authors
Mainline rail station (AOI) *	Binary (1 = present)	Mapped by the authors
Commuter rail station (AOI)	Binary (1 = present)	Mapped by the authors
Transit access time (in minutes)	Metric	Modeled by the authors based on GTFS data
Control variables		
Bus stop (POI)	Binary (1 = present)	OpenStreetMap contributors
Bus depot (AOI)	Binary (1 = present)	Mapped by the authors

Abbreviations: POI = Point of Interest; AOI = Area of Interest; GTFS = General Transit Feed Specification
* The mainline rail station also includes a commuter rail station.

these effects into our models. The decision to use bus depot locations as another control variable was driven by the fact that DRT trips made by DRT operator employees to or from these depots were included in the data set but could not be readily identified and filtered out. Therefore, we decided to account for this potential bias by using bus depot locations as a control variable.

Unfortunately, certain variables of theoretical interest could not be incorporated into our analyses. This applies, first, to large recreational areas and green spaces. While these areas could, in principle, have been distributed across multiple grid cells in a manner similar to university campuses or rail stations, they often lack clearly defined access points. As a result, the spatial distribution of pickup and drop-off locations associated with these areas was too dispersed to reliably distinguish meaningful demand concentrations from random patterns. We also excluded POIs belonging to the broad category of services. On the one hand, these POIs were too heterogeneous to be meaningfully treated as a single category. On the other hand, subdividing them into more specific categories (e.g., consumer services and public services) would have conflicted with our objective of maintaining parsimonious models and would likely have resulted in unstable estimates due to the small number of corresponding POIs within the study area.

Furthermore, we were unable to incorporate additional demographic or socioeconomic variables beyond the number of residents into our models. Previous studies have identified significant relationships between DRT usage and factors such as age, household composition, and income (e.g., Drake & Watkins, 2024; Ghimire & Bardaka, 2025b; Liezenga et al., 2024; Nelson & Phonphitakchai, 2012; Schneider et al., 2025; Thao et al., 2023; Wang et al., 2014). The most recent census in Germany provides publicly available spatial data containing variables such as age-group composition, average household size, and average rent per square meter, the latter of which could potentially serve as a proxy for socioeconomic status. However, due to data protection requirements and the limited sample sizes available at the highly granular grid-cell level, these variables were too incomplete and unreliable to be included in our analyses.

2.4. Statistical analysis

This study examines potential links between DRT demand and characteristics of the built environment using spatial regression models. Regression models represent the most widely used approach in the literature for investigating spatial determinants of DRT demand. However, different approaches exist regarding the use of ordinary regression models (Ghimire & Bardaka, 2025b; Kuehnel et al., 2025) versus spatial regression techniques (e.g., Gödde et al., 2023; Zwick & Axhausen, 2022), as well as regarding the appropriate specification of such spatial models. Given the granular resolution of our data, we expected variables to correlate with themselves across space ("spatial autocorrelation"), and therefore to require spatial regression models. The extent of spatial autocorrelation and the appropriate modeling approach are further discussed in **Section 3.1**.

We employ regression models both to analyze total DRT demand in southern Hamburg over the year 2024 (**Section 3.2**) and to examine demand within specific time-of-week periods (**Section 3.3**). To ensure comparability across models, the same set of independent variables is used in each specification. Variables that are not statistically significant are deliberately retained, as identifying built environment characteristics that do not significantly influence DRT demand at certain times is also of practical relevance. With regard to spatial spillover effects ("spatial lags"), we define all grid cells sharing either an edge or a corner as neighbors ("queen contiguity"). Consequently, each cell can have a maximum of eight neighboring cells. All statistical analyses were conducted in R 4.5 (R Core Team, 2025), using the packages *spdep* (Bivand, 2025), *sf* (Pebesma, 2025), and *spatialreg* (Bivand & Piras, 2025). To interpret potential relationships between built environment factors and DRT demand, p-values below 0.1 are considered indicative of statistical significance.

3. Results

3.1. Identification of the appropriate modeling approach

We anticipated that the data utilized for this study would reveal spatial dependencies that could not be adequately represented using ordinary least squares (OLS) regression and necessitated spatial regression analyses. To test this assumption, we first estimated OLS regression models for the influence of built environment characteristics on total DRT demand in 2024 (Table 2) and examined the distribution of the residuals.

Moran's I tests (Moran, 1950) indicated spatial autocorrelation of the residuals both for the number of DRT pickups (Moran's $I = 0.23$; $p < 0.001$) and the number of DRT drop-offs (Moran's $I = 0.21$; $p < 0.001$) at the grid cell level. Spatial regression models were therefore indeed necessary. To determine the appropriate model type for spatial regression analysis, we performed Lagrange multiplier (LM) tests (Anselin, 1988a). When considering DRT pickups (LM-Lag = 510.71; $p < 0.001$; LM-Error = 554.38; $p < 0.001$) and DRT drop-offs (LM-Lag = 415.03; $p < 0.001$; LM-Error = 458.01; $p < 0.001$), the results consistently showed spatial dependencies in the values of the dependent variable as well as in the error terms. Thus, we selected the Spatial Durbin Model (SDM), a

Table 2
Results of linear and spatial regression analyses examining the influence of built environment factors on total DRT demand in 2024.

Predictors	DRT pickups				DRT drop-offs			
	OLS		SDM		OLS		SDM	
	B	exp(B) − 1	B	exp(B) − 1	B	exp(B) − 1	B	exp(B) − 1
Intercept	1.85 ***	–	0.69 ***	–	1.82 ***	–	0.75 ***	–
Direct effects								
Residents (×10)	0.16 ***	0.18	0.13 ***	0.14	0.17 ***	0.18	0.14 ***	0.15
Workplaces (×10)	0.01 †	0.01	0.01 *	0.01	0.01 *	0.01	0.01 *	0.01
Grocery store	0.39 **	0.47	0.31 *	0.36	0.26 **	0.30	0.19 *	0.21
Retail store	0.54 ***	0.72	0.68 ***	0.98	0.34 ***	0.40	0.20 ***	0.22
Cultural institution	0.30 †	0.35	0.24 †	0.27	0.28 *	0.33	0.16 †	0.18
Dining establishment	0.34 *	0.40	0.48 **	0.62	0.38 *	0.46	0.54 ***	0.72
School	0.53 ***	0.70	0.37 ***	0.45	0.71 ***	1.03	0.68 ***	0.98
University	0.28	0.33	0.49	0.64	0.24	0.27	0.47	0.61
Doctor's office	0.35 *	0.43	0.41 **	0.51	0.43 †	0.54	0.45 †	0.57
Hospital	1.45 ***	3.24	1.31 ***	2.72	1.96 ***	6.12	1.46 ***	3.31
Mainline rail station	3.06 ***	20.23	3.19 ***	23.27	2.80 ***	15.45	3.15 ***	22.33
Commuter rail station	1.98 ***	6.26	1.80 ***	5.05	1.69 ***	4.40	1.42 ***	3.16
Transit access time	0.03 **	0.03	0.03 **	0.03	0.04 ***	0.04	0.04 ***	0.04
Bus depot (CV)	1.83 ***	5.22	1.73 **	4.66	2.26 ***	8.58	1.98 ***	6.26
Bus stop (CV)	2.02 ***	6.51	1.99 ***	6.33	1.97 ***	6.15	1.93 ***	5.89
Spatial lags								
Residents (×10)	–	–	0.02 **	0.02	–	–	0.01 *	0.01
Workplaces (×10)	–	–	0.01	0.01	–	–	0.01 †	0.01
Grocery store	–	–	0.62 ***	0.86	–	–	0.35 *	0.42
Retail store	–	–	0.60 **	0.82	–	–	0.57 †	0.78
Cultural institution	–	–	0.49	0.63	–	–	0.21	0.24
Dining establishment	–	–	0.34 ***	0.41	–	–	0.45 ***	0.57
School	–	–	0.36	0.43	–	–	0.42	0.53
University	–	–	0.68	0.97	–	–	0.75	1.13
Doctor's office	–	–	0.09	0.09	–	–	0.24	0.28
Hospital	–	–	−0.24	−0.21	–	–	−0.30	−0.26
Mainline rail station	–	–	−1.22 ***	−0.70	–	–	−1.47 ***	−0.77
Commuter rail station	–	–	−0.39 **	−0.32	–	–	−0.81 ***	−0.56
Transit access time	–	–	0.02 †	0.02	–	–	0.01	0.01
Bus depot (CV)	–	–	0.59	0.80	–	–	0.56	0.75
Bus stop (CV)	–	–	0.44	0.55	–	–	0.30	0.34
ρ (spatial autocorrelation)	–	–	0.52 ***	–	–	–	0.48 ***	–
Model performance								
Adjusted R^2	0.433	–	0.534	–	0.420	–	0.510	–
AIC	10,917	–	10,476	–	11,133	–	10,752	–

CV = Control variable. Statistical significance is indicated by the following: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$.

model type that considers spatial dependencies in both the dependent variable and the independent variables, as the appropriate modeling approach for our spatial regression analyses (Anselin, 1988b; LeSage & Pace, 2009).

The results of the SDMs for the impact of built environment factors on total DRT demand in 2024 are shown in Table 2. As anticipated, the SDMs revealed a statistically significant positive autocorrelation of the respective dependent variable, along with statistically significant spatial lags for multiple independent variables, when considering both the DRT pickup and DRT drop-off models. Consequently, both SDMs resulted in a substantial improvement in explanatory power compared to the respective OLS models. However, OLS models and SDMs estimated generally similar parameters for the direct effects of built environment factors. Therefore, the remainder of the Results section will focus exclusively on the SDMs.

3.2. Built environment factors and total DRT demand

Given the strong correlation between the numbers of DRT pickups and drop-offs at the grid cell level (see **Section 2.2**), it is not surprising that the two SDMs used to investigate the influence of built environment factors on these numbers arrived at similar results (Table 2). As the estimated coefficients (B) refer to logarithmic values of DRT pickups or drop-offs, we transformed these coefficients back (using exp[B] − 1) to obtain the semi-elasticity, allowing for better interpretability of the results.

The semi-elasticity indicates the average relative change in the number of DRT pickups or drop-offs when the respective independent variable increases by one unit — or by ten units in the case of residents and workplaces. For instance, an increase of ten individuals in the residential population of a cell led, all other things being equal, to an average of 14% more pickups and 15% more drop-offs in the same cell over the course of 2024. Conversely, increasing the number of workplaces by ten resulted in an average growth of only one percent in both the numbers of pickups and drop-offs in the same cell. For binary variables such as points of interest, the semi-elasticity refers to the relative change in DRT demand given the presence of at least one corresponding POI in a cell compared to the absence of such a POI. For example, according to our models, the presence of at least one doctor's office in a cell increased the annual number of DRT pickups in the same cell by an average of 51% and the number of drop-offs by 57%.

With the exception of the university campuses, which showed no statistically significant association with DRT demand, all of the characteristics of the built environment examined had a positive impact on the number of DRT pickups and drop-offs in their respective cells. In addition to bus stops and bus depots as control variables, mainline rail stations, commuter rail stations, and hospitals had the strongest effects. Transit access time also exerted a significant positive influence on DRT demand; for every additional minute of access time to fixed-route public transportation, the number of DRT pickups and drop-offs in the corresponding cell rose by an average of 3% and 4%, respectively. Similarly, grocery and retail stores had a positive impact on DRT demand; however, they increased the number of pickups considerably more than the number of drop-offs.

Beyond the direct effects, the results of the SDMs revealed a number of significant spatial lags; certain built environment factors thus appeared to influence DRT demand in neighboring cells as well. In the case of grocery stores, spillover effects were even more pronounced than direct effects in both the DRT pickup and DRT drop-off model. For retail stores, spillover effects were only more pronounced than direct effects in the DRT drop-off model. Conversely, the mainline rail station and commuter rail stations exhibited a *negative* impact on DRT demand in neighboring cells, highlighting the substantial concentration of DRT demand at these stations.

3.3. Temporal variation in the significance of built environment factors

Table 3 presents the findings of the spatial regression analyses conducted to assess the impact of built environment factors on DRT demand during five selected time-of-week periods. In addition to the control variables of bus stops and bus depots, only the mainline rail station, commuter rail stations, hospitals, and the number of residents had significant positive effects on DRT demand in their respective cells in all five TOWPs considered. As outlined in Section 3.2, rail stations exhibited a positive direct impact on their own cells while generating a negative spillover effect on neighboring cells — this observation was consistent across all five TOWPs.

In stark contrast, the positive effects of workplaces and schools on DRT demand were temporally limited and direction-dependent: during the weekday morning period, both factors increased the number of DRT

Table 3
Results of spatial regression analyses examining the influence of built environment factors on DRT demand in five time-of-week periods. For ease of presentation, the table only shows the regression coefficients and, where applicable, their statistical significance.

Predictors	Weekday morning period Mon–Fri, 6:00 AM–9:00 AM		Weekday afternoon period Mon–Fri, 3:00 PM–6:00 PM		Weekend nighttime period Fri–Sat, 8:00 PM–12:00 AM		Saturday afternoon period Sat, 3:00 PM–6:00 PM		Sunday evening period Sun, 5:00 PM–8:00 PM	
	Pickups	Drop-offs	Pickups	Drop-offs	Pickups	Drop-offs	Pickups	Drop-offs	Pickups	Drop-offs
Intercept	0.21 ***	0.13 **	0.24 ***	0.29 ***	0.20 ***	0.21 ***	0.09 ***	0.09 ***	0.09 ***	0.08 ***
Direct effects										
Residents (×10)	0.09 ***	0.03 ***	0.06 ***	0.08 ***	0.06 ***	0.09 ***	0.04 ***	0.03 ***	0.03 ***	0.04 ***
Workplaces (×10)	0.00	0.02 ***	0.01 ***	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Grocery store	0.18	0.24	0.41 *	0.24 *	−0.16 *	−0.13 **	0.43 ***	0.23 *	−0.04	−0.18 †
Retail store	0.26	0.40 ***	0.84 ***	0.22 ***	−0.28 **	−0.33 ***	0.69 ***	0.49 ***	−0.24 **	−0.27 ***
Cultural institution	0.15	0.35	0.25 *	0.09 *	0.17 †	0.14 *	0.20 **	0.13 *	0.01	0.06
Dining establishment	−0.04	0.19	0.16 †	0.43 ***	0.52 ***	0.29 ***	0.15 *	0.40 ***	0.25 ***	0.22 ***
School	0.23	1.21 ***	1.28 ***	0.22	−0.05	−0.07	0.01	0.06	−0.03	0.12
University	0.33	0.56	0.41	0.53	−0.10	−0.25 †	0.11	0.59	0.08	0.07
Doctor's office	0.45 **	0.50 ***	0.67 ***	0.51 ***	−0.26	−0.23	0.14	0.18	0.27	0.10
Hospital	0.58 **	0.82 ***	0.95 ***	0.93 ***	0.31 ***	0.44 ***	0.50 **	0.75 ***	0.58 **	0.39 **
Mainline rail station	2.74 ***	2.89 ***	2.62 ***	2.77 ***	2.04 ***	1.84 ***	1.44 ***	1.37 ***	1.48 ***	1.20 ***
Commuter rail station	1.68 ***	1.02 **	1.16 **	1.45 ***	1.07 ***	0.76 **	0.59 **	1.03 ***	0.96 ***	0.55 **
Transit access time	0.01	0.01	0.01	0.00	0.03 **	0.04 ***	0.00	0.01	0.02 *	0.03 ***
Bus depot (CV)	0.75 *	1.01 ***	1.07 **	1.18 **	0.50 *	0.66 ***	0.78 ***	0.90 ***	0.62 ***	0.65 ***
Bus stop (CV)	1.03 ***	1.21 ***	1.45 ***	1.23 ***	1.11 ***	1.09 ***	0.65 ***	0.69 ***	0.61 ***	0.52 ***
Spatial lags										
Residents (×10)	0.02 †	0.01 *	0.01 †	0.02 *	0.00	0.01	0.01 **	0.00	0.00	0.00
Workplaces (×10)	0.01	0.02 ***	0.01 **	0.01	0.01	0.00	0.00	0.00	0.00	0.00
Grocery store	0.23	−0.19	0.45 **	0.19 †	−0.13 †	−0.58 **	0.68 **	0.44 †	−0.56 **	−0.34 *
Retail store	−0.24	0.18 **	0.90 **	0.38 ***	−0.23 **	−0.15	0.53 **	0.49 **	−0.14	−0.03
Cultural institution	−0.04	0.28	0.45	−0.08	0.07	0.16 **	0.41 *	0.32 †	−0.12	−0.31
Dining establishment	−0.08	0.03	0.39 ***	0.51 ***	0.39 *	0.55 **	0.34 *	0.43 ***	0.29 *	0.40 ***
School	0.26	0.53 ***	0.32	0.07	−0.14	−0.25	−0.37	−0.19	−0.02	−0.14
University	−0.16	0.58	0.44	−0.04	−0.09	−0.20	−0.21	−0.31 *	−0.17	−0.28
Doctor's office	0.32	0.14 **	−0.09	0.08	0.21	−0.02	0.08	0.23	−0.10	0.08
Hospital	−0.17	0.09	−0.23 †	−0.04	0.03	−0.09	0.13	−0.20	0.24	−0.10
Mainline rail station	−0.60 **	−0.76 **	−0.51 *	−0.62 **	−0.75 **	−0.99 ***	−0.59 *	−0.72 **	−0.60 ***	−0.81 ***
Commuter rail station	−0.13 *	−0.24 *	−0.22 **	−0.31 ***	−0.19 *	−0.20 †	−0.16 **	−0.40 ***	−0.15 †	−0.26 **
Transit access time	0.01	0.00	0.00	0.00	0.03 **	0.01 *	0.00	0.00	0.01 †	0.00
Bus depot (CV)	0.41	0.12	0.51	0.25	−0.42	−0.23	−0.05	0.20	0.18	0.04
Bus stop (CV)	0.36 **	0.12	0.18	0.05	0.01	0.22	0.06	0.19	0.16	0.24 †
ρ (spatial autocorrelation)	0.40 ***	0.21 ***	0.39 ***	0.34 ***	0.27 ***	0.38 ***	0.27 ***	0.25 ***	0.18 ***	0.24 ***
Model performance										
Adjusted R^2	0.373	0.378	0.436	0.415	0.451	0.446	0.339	0.324	0.318	0.320
AIC	8,493	7,735	8,275	8,528	6,469	7,177	4,773	4,794	4,510	4,874

CV = Control variable. Statistical significance is indicated by the following: *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$; † $p < 0.1$.

drop-offs, while during the weekday afternoon period, they increased the number of DRT pickups; outside these periods, however, they had no significant impact. The positive influence of transit access time on DRT demand appeared to be limited to certain TOWPs as well. Specifically, a longer access time to fixed-route public transportation only increased DRT demand during the weekend nighttime period and the Sunday evening period, that is, only in TOWPs with a tendency toward weaker fixed-route public transit service. In the other three TOWPs, we found no statistically significant relationship between transit access time and DRT demand.

The impact of grocery stores and retail stores on DRT demand was positive, particularly during the weekday afternoon period and Saturday afternoon period. Outside of their typical opening hours, specifically during the weekend nighttime period and Sunday evening period, these stores significantly reduced DRT demand both in their own cell and in their neighboring cells. Doctors' offices only increased DRT demand during the weekday morning and weekday afternoon periods; in the other TOWPs, doctors' offices had no statistically significant effect. Restaurants had a positive influence on DRT demand in all TOWPs, with the exception of the weekday morning period. Cultural institutions also had a positive impact on DRT demand in all TOWPs, except for the weekday morning period and the Sunday evening period.

4. Discussion and conclusion

4.1. Key findings and implications

This study investigated the influence of built environment characteristics on DRT demand utilizing data on pickup and drop-off locations from an existing DRT service in southern Hamburg, Germany. We employed fine-grained spatial regression analyses to identify spatial determinants of the total DRT demand throughout the year 2024. Additionally, we conducted analyses for five selected time-of-week periods, with the aim of investigating temporal variations in the significance of built environment factors — a subject that has received limited attention in previous research. Spatially and temporally detailed findings on the effects of the built environment on DRT demand can inform planning and operation of DRT services to allocate resources more cost-effectively.

The granular level of our analyses enabled us to identify statistically significant relationships with DRT demand for nearly all of the characteristics of the built environment that we considered. Although the identified spatial relationships are not particularly surprising and generally follow expected temporal patterns, they still yield several implications for practice and further research.

Consistent with prior research (Gödde et al., 2023; Imhof & Blättler, 2023; Thao et al., 2023; Zubair et al., 2025; Zwick & Axhausen, 2022), our findings suggest that rail stations are the primary sources and destinations of DRT demand. This was evident in the consistently strong and positive effects of rail stations on DRT demand in all periods examined. It was also indicated by the observation that rail stations appeared to concentrate DRT demand to such an extent that they even reduced the number of DRT pickups and drop-offs in their neighboring areas. Overall, these results suggest that, even in service areas where numerous other points of interest exist in addition to rail stations and where the DRT service is not exclusively designed as a feeder to rail-based public transit, rail stations nevertheless remain the dominant focal points of DRT demand.

As in previous studies (Ghimire & Bardaka, 2025b; Gödde et al., 2023; Imhof & Blättler, 2023; Wang et al., 2023; Zwick & Axhausen, 2022), our work identified population hotspots as another primary driver of DRT demand. This effect was consistent across all periods examined. However, this does not necessarily imply a positive association between the degree of urbanization and DRT demand. Instead, it likely reflects the fact that a higher concentration of residents results in a higher number of potential DRT users. Our research also demonstrated that areas with longer access times to fixed-route public transportation — typically *less* urban areas — generated a significantly higher demand for DRT. Notably, the positive impact of transit access time was only evident in time-of-week periods where public transportation services tend to be less frequent, namely during nighttime hours and on Sundays. From these findings, different implications for the operation of DRT systems can be derived. On the one hand, our results show that DRT can effectively compensate for gaps in fixed-route public transportation during off-peak hours. On the other hand, the absence of a significant effect of transit access time during weekday peak hours suggests that DRT is at least partly used as a substitute for conventional public transportation. DRT operators should seek to mitigate such cannibalization on the supply side. For instance, during peak hours, the booking platform could be configured to prevent requests for trips that can be made by conventional public transit within an acceptable level of service.

According to existing research, areas with a higher concentration of jobs usually constitute important centers of DRT demand as well (Imhof & Blättler, 2023; Liezenga et al., 2024; Zwick & Axhausen, 2022). Our findings appear to offer a more nuanced perspective on this matter. In line with other studies, we identified a positive relationship between the number of workplaces in an area and DRT demand. Yet, in our study, this relationship was only statistically significant during weekday morning and afternoon periods. The effect of workplaces was also direction-dependent and relatively weak. It should be noted, however, that a considerable proportion of workplaces in our study area were likely already captured indirectly in the regression models through other variables such as POI locations.

Our findings were more closely aligned with previous research on the positive impact of health-related facilities on DRT demand. Corroborating the results of other studies (Ghimire & Bardaka, 2025b; Imhof & Blättler, 2023; Ryley et al., 2014; Thao et al., 2023; Zwick et al., 2023), we identified hospitals and doctors' offices as drivers of DRT demand. Our analyses further showed that, in contrast to doctors' offices, hospitals were important origins and destinations for DRT trips even on weekends and in the evening hours. The available data did not allow us to draw conclusions about which user groups rely on DRT for trips to or from health-related points of interest. It is nevertheless plausible that these trips are predominantly made by individuals with health-related mobility impairments, particularly older adults, as has been shown in previous studies (e.g., Liezenga et al., 2024; Nelson & Phonphitakchai, 2012; Thao et al., 2023; Wang et al., 2014). This highlights the importance of designing DRT systems to be as accessible as possible, for example with regard to booking options and vehicle models.

To the best of our knowledge, the role of schools as a spatial determinant of DRT demand had not been investigated previously. Given the fact that the DRT service we studied could also be used by minors unaccompanied by adults due to the availability of prepaid cards, schools represented a potential catalyst for DRT demand in our case study. Our findings indicate that schools did indeed have a positive influence on the number of DRT drop-offs and pickups, although this relationship was only statistically significant during weekday morning and afternoon periods. These findings allow for both positive and more critical interpretations. On the one hand, they may indicate that DRT services enable greater independent mobility for minors, particularly if they substitute for parental escort trips by car. On the other hand, relatively strong DRT demand associated with schools during peak hours could also lead to capacity constraints that affect users who rely on DRT, such as individuals with mobility impairments. Against this background, further research on DRT usage by minors and its implications for individual mobility and overall system performance appears warranted.

Other drivers of DRT demand, according to existing research, include commercial and leisure-related points of interest such as shops, restaurants, and cultural institutions (Gödde et al., 2023; Imhof & Blättler, 2023; Liezenga et al., 2024; Thao et al., 2023; Zwick & Axhausen, 2022). Our findings corroborate previous conclusions while providing more detailed insights into these dynamics. For instance, our analyses indicate that grocery and retail stores increase the number of DRT pickups more than the number of DRT drop-offs, suggesting that transporting purchases is a more prevalent use case than traveling to the stores. DRT operators should therefore ensure that their vehicles provide sufficient space not only for passengers but also for their shopping items.

During nighttime hours and on Sundays, when these establishments are typically closed, grocery and retail stores had a negative impact on DRT demand. Furthermore, the effects of grocery and retail stores, as well as restaurants and cultural institutions, on DRT demand in their surrounding areas tended to be even more pronounced than their effects at their own locations. This may be explained, at least in part, by the fact that many of these POIs in our study area were located in areas not directly accessible by DRT, such as pedestrian zones or shopping centers.

4.2. Limitations

When interpreting our results, it is important to consider the methodological limitations of our research. A key limitation of this study is that, despite the high spatial resolution of the analyses and the general consistency of our findings with the existing literature, the results do not allow for any definitive conclusions regarding causal relationships. It should be noted that facilities located at DRT pickup or drop-off locations may not necessarily correspond to the actual origins or destinations of trips made by DRT users. This issue is particularly pronounced in more urban areas of the study region, where multiple points of interest are often located in close proximity to one another.

Another important limitation concerns the OpenStreetMap data used in this study, which did not contain detailed information on the size or specific subtype of certain points of interest, such as grocery stores. It is reasonable to assume that large supermarkets may generate higher DRT demand than smaller convenience stores; however, such differences could not be accounted for in our models. Furthermore, as outlined in Section 2.3, we were unable to incorporate more detailed demographic and socioeconomic variables into our regression models due to the lack of information beyond the number of residents at the grid-cell level. In addition, certain POI categories, such as services and recreational areas, could not be included in our analyses. Spatially and temporally high-resolution studies that integrate a broader range of built environment characteristics as well as more detailed demographic data would therefore represent a valuable extension of the present work.

Finally, it should be noted that our findings are based on a single case study of one DRT service and are therefore subject to the typical strengths and limitations associated with case study research. While this design allowed us to analyze DRT usage in a real-world setting, the results are context-specific and may not be fully transferable to other services or operating environments. This is exemplified by the fact that the DRT service analyzed in this study is exclusively app-based. Previous research has shown that, particularly among older adults, there is a preference for alternative booking and payment options, such as telephone booking and payment on board the vehicle (Jittrapirom et al., 2019). The data provided by the DRT operator did not allow for any conclusions regarding the demographic characteristics of users. However, it is reasonable to assume that the operational characteristics of the service also influenced its user composition and, consequently, the spatial and temporal patterns of DRT demand. Furthermore, the DRT service examined in this study was a heavily subsidized pilot project and thus relatively affordable to use, which likely influenced user characteristics and usage patterns as well. Under more market-oriented pricing conditions, the observed patterns of DRT demand might have differed. This study should therefore be understood as one building block that, together with further studies of DRT services in different contexts, contributes to a more comprehensive understanding of DRT usage.

Data availability

The DRT trip data used in this study is confidential.

CRediT authorship contribution statement

Felix Czarnetzki: Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Leonie Dittrich:** Writing – review & editing, Formal analysis, Data curation, Conceptualization. **Ole Röntgen:** Writing – review & editing, Formal analysis, Conceptualization. **Tyll Diebold:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Carsten Gertz:** Writing – review & editing, Supervision, Funding acquisition.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work the authors used ChatGPT and DeepL in order to improve readability and language. After using these tools, the authors reviewed and edited the content as needed and take full responsibility for the content of the publication.

Declaration of competing interest

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

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