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Analysis of Location-based Accessibility using a Mobile Phone-Based Origin-Destination Matrix and a Land Use Map

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Abstract

As dynamic accessibility depends on the interplay of opportunities and travel impedance, available General Transit Feed Specification data and mobile phone data offer new opportunities to enhance the temporal sensitivity of accessibility. This paper utilises a mobile phone-based origin-destination matrix and dynamic travel time via public transport to explore spatial and temporal patterns of accessibility measures. Four scenarios are constructed and compared to illustrate the relative accessibility. The results show that the impact of the public transport system changes progressively depending on the cut-off time considered, and average accessibility gains could vary four-fold between the city centre and suburban zones. Besides, the exploration of the relationship between land use, mobile phone-based attractiveness, and dynamic accessibility underlines the time-dependent effect of land use. Future research should focus on the development of advanced accessibility-based travel models.

1. Introduction

Accessibility is a key criterion for evaluating how well a transport system serves different categories of users (Morris et al., 1979). In the context of passenger transport, Geurs and van Wee (2004) define accessibility as the extent to which land use (LU) and transport systems enable (groups of) individuals to reach activities or destinations via one or more transport modes. Following this definition of accessibility, ideally, accessibility measures should incorporate all components of the urban system: LU, transport networks, temporal dynamics, and individual constraints. However, in practice, accessibility assessments often focus on a subset of these components, depending on the perspective taken. Hansen (1959) conceptualises accessibility as “the potential of opportunities for interaction”. Specifically, accessibility is defined as being directly proportional to the size of the activity (e.g., number of jobs) at the destination and inversely proportional to some function of impedance (e.g., distance or travel time) between origin and destination. A common opportunity-based alternative is the cumulative opportunity measure, which counts the number of activity destinations reachable within a specified travel time or distance from a given origin (Chen et al., 2011). In essence, opportunity-based accessibility captures the extent of the attractiveness of each potential destination from a given location and has been extensively adopted as location-based measures (also referred to as activity-based or place-based) (Vandenbulcke et al., 2009; Hu and Downs, 2019) at a macro level.

As spatial and temporal constraints significantly shape people’s access to activity locations, person-based accessibility research has emerged as a complementary perspective. Rooted in space-time geography (Hägerstrand, 1989), this approach emphasises individual space-time constraints (Kwan et al., 2003) and models how people plan and conduct flexible activities depending on where, when, and with whom they engage in these activities (Neutens et al., 2010). However, widespread adoption of this approach has been limited due to the lack of high-resolution individual travel data required for robust implementation (Neutens et al., 2011). In comparison to person-based accessibility, location-based models have traditionally struggled to account for temporal constraints due to the limited availability of time-sensitive spatial data (Järv et al., 2018; Hu and Downs, 2019). In recent years, however, the emergence of data such as General Transit Feed Specification (GTFS) data and mobile phone data (MPD) has opened up new possibilities for incorporating temporal dynamics into location-based accessibility analysis.

MPD used in travel behaviour research generally originate from two sources: event-driven data from mobile network operators and sensor–based data from smartphones (Wang et al., 2018). The former data are generated during voice or data events, while the latter are typically collected through third-party mobile applications that offer location-based services. MPD have been increasingly applied in studies, ranging from travel demand modelling to the analysis of human mobility patterns. For instance, Bwambale et al. (2019) developed a demographic group prediction model using call detail records (CDR) as part of a latent class model for trip generation. Although such models show potential for creating synthetic populations, they often require subsamples with known demographic characteristics, which are rarely available. Moreover, MPD present limitations, including coarse spatial granularity, uncertain demographic representation, and the absence of a clear ground truth (Chen et al., 2016). Consequently, researchers have explored data fusion methods to combine MPD with other sources in transport planning (Kuhnimhof et al., 2024). Notably, aggregated travel demand estimates derived from MPD generally align well with results from conventional travel surveys (Dypvik Landmark et al., 2021; Fekih et al., 2022).

Urban LU, encompassing commercial, industrial, residential, and transport categories, shapes local trip generation and attraction dynamics. Conventional four-step travel demand models

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use LU characteristics to estimate movement volumes between traffic analysis zones (TAZs) (McNally, 2000). Numerous studies have examined the impact of LU on trip generation, distribution, and travel demand model sensitivity (Bernardin and Conger, 2010; George and Kattor, 2013). Non-physical factors, such as socioeconomic and demographic characteristics, also influence destination choice and trip volume. Population density, for example, is closely associated with LU mix, walkability, transit service levels, and parking availability (Moudon et al., 2005). Employment and population counts are sometimes used as proxies for LU intensity (Shi and Zhu, 2019). Even modest changes in LU mix can lead to significant shifts in mobility behaviour (Sarkar and Chunchu, 2016). Greater LU intensity typically increases the number of trips, congestion, and travel time (Gao et al., 2021). Although improved accessibility, accompanying higher densities and mixed uses, may paradoxically increase vehicle trips (Ewing et al., 1996). The LU-travel relationship remains complex, with studies yielding mixed findings. Despite growing interest in the link between LU and transport, the dynamic interplay between LU and time-varying accessibility, especially via public transport, remains under-explored. This study addresses that gap by combining GTFS-based travel time data with a cumulative opportunity framework. Using the province of Liège, Belgium, as a case study, we evaluate the impact of LU and public transport scheduling on spatial and temporal accessibility patterns. The proposed framework offers planners a replicable method for analysing the trade-offs between LU and transport policy decisions, supporting the development of more equitable and time-sensitive urban mobility strategies.

2. Related work

In recent years, time-varying location-based accessibility indicators have been developed to account for dynamic demand, supply, and transport system changes. For example, Vandenbulcke et al. (2009) examined accessibility by car along the Belgian road network from each commune to two destination types: major cities and railway stations. They calculated generalised travel time by weighting network elements and station accessibility based on speed limits and service frequency, separately for peak and off-peak periods. Hu and Downs (2019) proposed a place-based space-time job accessibility measure based on a modified gravity model, integrating the ratio between job supply and workforce demand. They discretised job and population data at fine spatial and temporal resolution, and calculated hourly travel times from Google Maps to derive dynamic job accessibility. Their approach enables the analysis of spatio-temporal job imbalances and the assessment of the impact of policies such as flexible working hours and mixed LU development. Similarly, Tenkanen et al. (2016) examined travel times by car and public transport to the nearest open grocery store offering healthy food. Cumulative accessibility curves, which show the percentage of the population within a given travel time, were used to analyse both modal and temporal effects on accessibility. Järv et al. (2018) modelled location-based accessibility using travel times via public transport between people's locations and grocery stores. Unlike Tenkanen et al. (2016), they used only public transport and incorporated mobile phone CDR to estimate dynamic population presence. Their results were compared with static accessibility models based on population register data. Lee et al. (2018) conducted an empirical study of spatial accessibility using mobile phone-derived population data and real-time bus schedules during peak and late-night periods. A distance-decay function was applied to reflect varying perceptions of travel time depending on proximity to bus stops. Accessibility scores were computed for each population unit based on proximity and service availability.

Smart card data, too, provide valuable insights into the temporal variability of public transport accessibility. For instance, Arbex and Cunha (2020) used smart card transactions, GTFS schedules, and GPS-based automatic vehicle location (AVL) data to estimate boarding and alighting points and analyse how crowding and travel time variability affect job accessibility via cumulative opportunities. García-Albertos et al. (2019) combined Google Maps travel time estimates with mobile phone-based origin-destination (OD) matrices to construct dynamic accessibility scenarios. They isolated the influence of two components: (*i*) the attraction mass, based on the number of mobile phone trips, and (*ii*) variable travel times by car across the day.

From the literature, several common approaches to location-based accessibility emerge. First, network-based metrics are used to evaluate travel time or distance to specific destinations. Second, opportunity-based accessibility combines a measure of attraction (e.g. number of jobs, service, or arrivals), with travel cost. Third, dynamic (time-varying) accessibility extends these measures by incorporating temporal variations in demand, supply, or network performance, typically via public transport or road networks. Opportunity data can be drawn from a range of sources, including (*i*) activity-specific trip counts from surveys; (*ii*) open datasets, such as the number of jobs, services, or facilities; and (*iii*) population presence or trip arrivals derived from MPD. As data availability and computational capacity increase, accessibility modelling has shifted toward higher resolution and more temporally sensitive indicators. In addition, competitive factors, such as demand pressure or crowding, are increasingly incorporated into accessibility metrics through mechanisms like supply–demand ratios.

Despite these advances, challenges persist in capturing intraday dynamics of both travel time and demand. This study builds on recent work by integrating mobile phone-derived OD matrices, GTFS-derived public transport travel times, and LU data from a web mapping portal. Although proprietary MPD is used, the framework is adaptable to open mobility datasets, increasing its broader applicability. We estimate and map time-sensitive accessibility in Liège using mobile phone-derived trips and dynamic public transport travel times. In addition, we investigate the relationship between LU and both mobility demand and accessibility outcomes. The analysis supports the use of dynamic, location-based accessibility measures to enhance the responsiveness of travel demand models, particularly by incorporating feedback in mode and location choice components. This study also serves as a foundation for the development of accessibility-based transport models with reduced data requirements and improved temporal realism.

3. Methodology

3.1 Data

The overall methodological framework for this research is presented in Figure 1. The province of Liège, located in the easternmost part of Wallonia, Belgium, borders the Netherlands, Germany, Luxembourg, and five other Belgian provinces.

It consists of four administrative districts, comprising 84 municipalities, with the city of Liège as the capital (Figure 2). Hourly mobile phone-based OD matrices are available for an average weekday (7 days x 24 hours), aggregated from observations collected between 15 January 2018 and 8 February 2018. The MPD originate from network operator Proximus, which holds approximately 40% of the Belgian telecom market. The signalling data provided by Proximus to Service public de Wallonie (SPW) Mobilité et Infrastructures were aggregated into 310 mobile phone cells within the province. Each OD matrix captures the number of trips originating from and arriving at each cell, aggregated by hour.

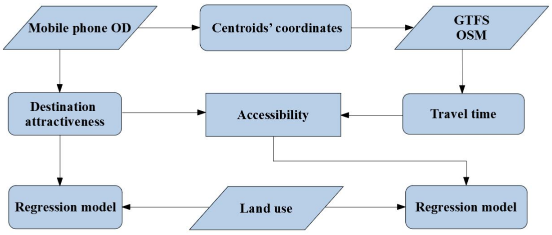


Figure 1. The research framework.

In this study, mobile phone cells are spatially represented by their centroids. To understand spatial variation in destination attractiveness, we compute and map the average daily trip rate by dividing the daily mean number of arrivals by the population present at midnight. As shown in Figure 3, the zone corresponding to central Liège exhibits the highest trip rate (4.41), indicating strong spatial centrality.

Next, we use the `r5r` package to compute public transport travel times for each hour on weekdays, aligning with the temporal resolution of the MPD. The `r5r` framework constructs a multimodal network based on OpenStreetMap (OSM) for the street network and GTFS data for scheduled public transport services (Pereira et al., 2021). Travel times are calculated from each OD pair at each departure hour, considering all minute-level departures within a one-hour time window. Median travel times are retained by default, and walking time is capped at 30 minutes. Note that the Liège province spans a large area (3,857 km^2) and is served by two independent public transport agencies: the SNCB (national railway) and TEC (regional bus). As SNCB mainly provides intercity connections, some intra-provincial OD pairs may lack feasible public transport routes. In such cases, where no route can be identified or travel cannot be completed within a reasonable time window, the travel time is marked as infinite, indicating that the destination cannot be reached within a day with the given origin.

To assess the influence of LU data on accessibility, we integrate LU and land cover (LC) data provided via the Walloon geoportal WalOnMap. These data follow the Hierarchical INSPIRE Land USE Classification System (HILUCS), which offers a multi-level nomenclature of LU and LC based on natural, infrastructural, and economic attributes (Beaumont et al., 2021). At Level 1, the nomenclature includes (*i*) Primary production, (*ii*) Secondary production, (*iii*) Tertiary production, (*iv*) Transport Networks logistics and utilities, (*v*) Residential use, (*vi*) Other uses, and (*vii*) Natural areas. The province of Liège is predominantly characterised by Primary production (about 77.74%), including Agriculture (about 49.73%),

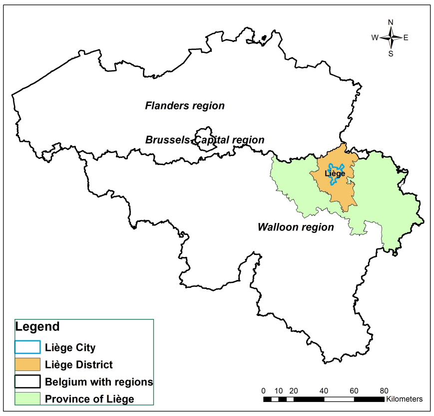


Figure 2. Location of Liège in Belgium.

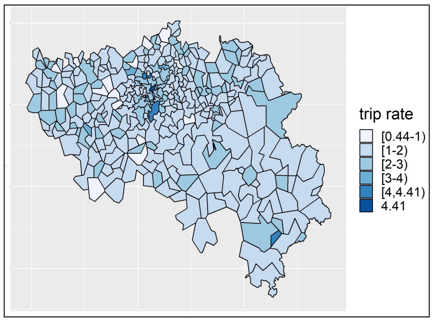


Figure 3. Daily mean number of arrivals per inhabitant in the province of Liège.

Forestry (about 27.65%), and Other primaries (about 0.36%) at Level 2 (Figure 4). However, the LU profile around the district of Liège is dominated by residential use and tertiary services. Therefore, we further divide LU into Level 3 and derive 48 types of LU. Notably, the district of Liège, our primary focus, accommodates approximately 56.5% of the province's 1.1 million residents and contains all Level 3 LU types (see orange area in Figure 2).

To link LU with MPD, we first convert the LU feature to raster data with a spatial resolution of one meter by one meter. As a result, each square of the raster map has a unique LU type. Thereafter, we overlay the raster map over the vector map of

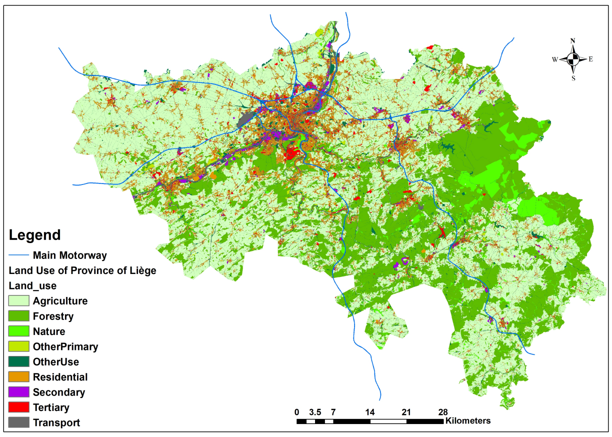


Figure 4. Land Use of the province of Liège at Level 1 and Level 2.

mobile phone networked areas (cells) and apply the GIS zonal statistics tool to aggregate the number of each type of LU raster parcel to each cell. Thus, we obtain parcel counts of different LU in each mobile phone cell.

3.2 Regression analysis

To explore how LU influences travel demand, we conduct multiple linear regression analysis, using MPD-derived arrivals as the dependent variable and LU variables as predictors. Before estimation, we test for multicollinearity using the variance inflation factor (VIF) using the R package "car", with a conservative exclusion threshold of VIF > 5. This results in the removal of 14 highly collinear LU categories. This means that 14 categories of LU (land use) that are highly correlated with each other have been removed to reduce redundancy. The remaining 34 categories will be used in the next step of the regression analysis to ensure more reliable and interpretable results.

As hourly mobile phone-based OD matrices are available, we first aggregate the five weekday (Monday to Friday) OD matrices to a one-day matrix (1 average weekday x 24 hours). To examine temporal effects, we define three time periods of departure times: (*i*) morning peak (06:00–09:00), (*ii*) midday off-peak (11:00–14:00), and (*iii*) afternoon peak (15:00–18:00). The dependent variable in each regression model is the total number of arrivals within a given time window. After applying VIF-based variable reduction, we fit ordinary least squares models for each time period and perform stepwise regression to retain only statistically significant LU predictors, ensuring parsimony and interpretability.

3.3 Measuring accessibility

Accessibility is modelled using a cumulative opportunities framework. A simple cumulative opportunities measure from one origin i to a set (n) of destinations at time t is defined by Equation 1 and Equation 2 (García-Albertos et al., 2019; Wessel and Farber, 2019)

$$A_{i,h} = \sum_{j}^{n} W_j \cdot f(T_{ijh}) \tag{1}$$

$$f(T_{ijh}) = \begin{cases} 1, & \text{if } T_{ijh} < \theta \\ 0, & \text{otherwise} \end{cases} \tag{2}$$

where $A_{i,h}$ is the accessibility of origin point i calculated as the mean value across five consecutive weekdays for one-hour departure windows at departure time h; W_j is the attraction mass of destination point j, which in our study is the mobile phone-based total number of arrivals, and $f(T_{ijh})$ is an impedance function that denotes a binary measure of whether a destination j is accessible within a given time threshold θ. Cumulative accessibility is widely embraced by transport and urban planners or policy-makers as it is easy to compute and interpret (Kelobonye et al., 2020). To analyse temporal variation in accessibility,we compute accessibility scores for three representative time windows–morning peak (08:00-09:00), off-peak (13:00-14:00), and afternoon peak (17:00-18:00), using thresholds of 30, 60, and 90 minutes. In line with Pereira (2019), this allows us to test whether threshold selection significantly alters accessibility patterns and policy implications. To evaluate the temporal dynamics of accessibility, we compare four distinct scenarios: (*i*) mean arrivals and off-peak (midday) travel time (reference); (*ii*) mean arrivals and hour-specific travel time (dynamic congestion); (*iii*) hour-specific arrivals and off-peak travel time (dynamic attraction); and (*iv*) hour-specific arrivals and travel times (fully dynamic). Finally, we apply regression analysis to explore the relationship between LU and dynamic accessibility as defined in the fourth scenario. This provides insight into how spatial land use patterns shape time-sensitive accessibility outcomes.

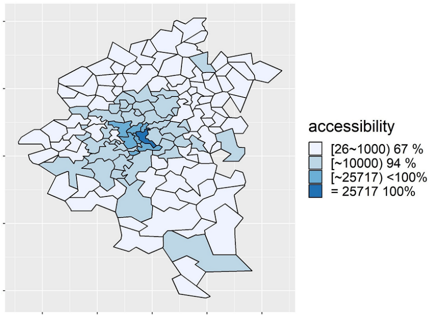
4. Results and Discussion

4.1 Accessibility by public transport

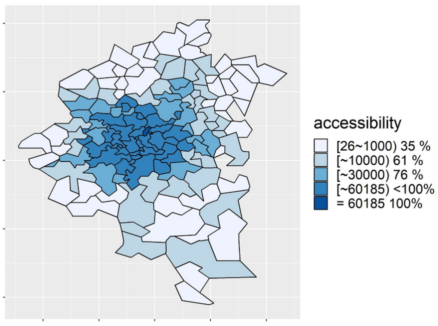
Accessibility is estimated using a cumulative opportunity approach, reflecting the number of destinations reachable within a specified travel time via public transport. The level of accessibility depends on the destination attractiveness, congestion, and the defined travel time threshold. Figure 5 visualises the spatial distribution of dynamic accessibility under various public transport time thresholds. The resulting patterns reveal a typical centre-periphery structure: central areas exhibit the highest accessibility, while peripheral areas are progressively less accessible via public transport.

As shown earlier (Figure 3), some peripheral zones in the district of Liège exhibit high trip rates (3-4 trips per day) despite their distance from the city centre. These areas are often located near major road exits and have a relatively high proportion of residential or tertiary areas. However, as the level of accessibility depends on travel time, apart from the opportunity feature, accessibility has an obvious centre-periphery pattern, especially in scenarios with a lower travel time threshold. Accessibility clearly improves as the travel time threshold increases. For example, the percentage of TAZs with accessibility measures below 10,000 decreases from 94% with a 30-minute threshold (Figure 5a), to 61% at 60 minutes (Figure 5b), and 28% at 90 minutes (Figure 5c).

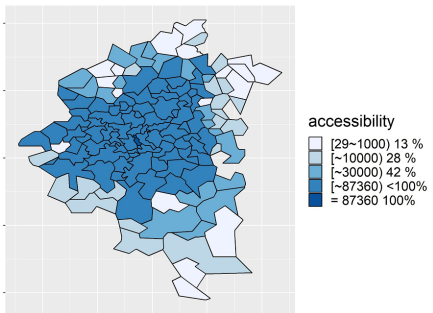
Moreover, time-sensitive accessibility can be evaluated by applying a travel time cut-off and adjusting both the attraction mass and public transport travel times. During the morning peak (08:00-09:00), accessibility levels are at their highest, followed by the afternoon peak and then off-peak periods. The zones with the greatest accessibility tend to be located around the Liège city centre, where the most important bus terminals are concentrated. These zones also feature a diverse LU mix, combining dense residential areas and commercial services. When applying a 30-minute travel time threshold, the proportion of TAZs with accessibility scores above 10,000 remains relatively stable across time slots, with only a few notable exceptions. One such exception is an enclave in the northern part of the district, which, despite being located in a peripheral area, demonstrates unexpectedly high accessibility(Figure 5a). Its favourable accessibility can be attributed to its proximity to a neighbouring city in the southeastern Netherlands, which enhances its connectivity. Conversely, some zones situated close to the urban core or with high trip-attraction rates display relatively low accessibility during peak hours due to extended travel times. In practice, this means that reaching key urban amenities such as universities or hospitals from these zones may require



(a) 8 AM with cut-off 30 min



(b) 8 AM with cut-off 60 min



(c) 8 AM with cut-off 90 min

Figure 5. Temporal variation in accessibility with various time thresholds at 8 AM in the morning for the district of Liège.

as much time as travelling from more distant peripheral municipalities. These findings suggest that low cut-off thresholds, such as 30 minutes, may inadequately reflect the average travel time required for residents in peripheral zones to access central urban opportunities (Arbex and Cunha, 2020). In contrast, a longer travel time threshold , such as 90 minutes, enables over 70% TAZs to reach an accessibility value above 10,000, regardless of the time of day. This outcome is intuitive, as longer time windows allow access to a broader set of destinations. Notwithstanding, the selection of a cut-off value should be context-specific and guided by normative assumptions regarding acceptable commute durations (Pereira et al., 2021).

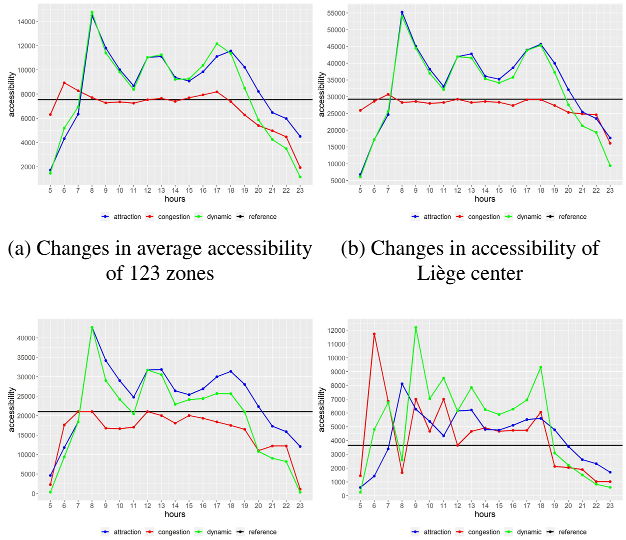
4.2 Comparison between accessibility scenarios

Zonal relative accessibility allows policy-makers to assess the geographic distribution of opportunities and transport services (Boisjoly and El-Geneidy, 2016). In this study, we compare accessibility across different times of the day by evaluating how accessibility is shaped by the joint effects of variations in travel time and attraction mass. To isolate the influence of each component, we define four accessibility scenarios in which one factor is held constant while the other varies. To facilitate comparisons between scenarios, we apply a fixed travel time cut-off of 60 minutes. However, in some instances, there are OD pairs that are either not served by public transport during certain hours or cannot be reached within a reasonable time frame, particularly for peripheral zones at night. Therefore, their public travel times cannot be derived from OSM and schedule-based GTFS. In such cases, travel time will be treated as infinite, and the OD pair is excluded from the calculation. The alternative option for average travel time, as a fixed factor, is the time at off-peak (12:00-13:00).

The first reference accessibility scenario is derived based on the mean attraction mass and the travel time during off-peak hours. Although both automobile and transit travel times fluctuate regularly due to congestion, transit travel times are uniquely affected by service provision variables such as vehicle headways, scheduling, and the synchronization of transfers (Farber et al., 2014). Therefore, the accessibility provided by a public transport system can differ from that provided by the road network with historical speed profiles such as the one given in Moya-Gómez et al. (2018). Nevertheless, a gap remains in evaluating the effect of congestion on accessibility by public transport. To answer this question, we map spatial and temporal patterns of relative accessibility measures for the morning peak (8:00-9:00 am) and afternoon peak (17:00-18:00 pm).

The second scenario (dynamic congestion) is constructed by fixing the attraction mass as the mean number of arrivals while varying the public transport travel time. The third scenario is called the dynamic attraction, which is defined by using the referencing travel time and the varying attraction mass. If variations in both public transport travel time and destination attraction mass are considered, this scenario is regarded as a fourth fully dynamic scenario. Lastly, the average accessibility measures from different scenarios are compared with those from the reference scenario. As a result, each transport zone has its own relative accessibility profile. The comparison presents very marked differences for some zones. To better interpret the temporal pattern of accessibility measures, we plot the curves of average accessibility values across the day for four scenarios at once (Figure 6a) suggested in Moya-Gómez et al. (2018). Meanwhile, we select three TAZs that are representative of the internal discrepancies in the district of Liège (with 123 zones) from the centre to the south, including 1) one of the Liège centres (Figure 6b); 2) a close outer part of the city called Sart-Tilman with a mix of land use of most important university education facilities and low residential density area (Figure 6c); 3) a suburban area called Esneux (Figure 6d).

In general, the average values of each scenario reveal that the variation in destination attractiveness outweighs the variation in congestion detected by public transport. The curve of the fully dynamic accessibility scenario is located closer to the attraction scenario than the congestion scenario and substantially higher than the average reference value during the daytime. In contrast, the negative influence of congestion on accessibility compared with the reference scenario happens particularly around 9:00 to 11:00 am and after 18:00 pm. Differences in the profiles of the different transport zones can be seen from Figure 6b to 6d. The central transport zone is affected by congestion starting from 8:00 am. This area contains economic activities and is more sensitive to congestion at 16:00 pm due to the outbound journeys. The second transport zone with educational facilities



(a) Changes in average accessibility of 123 zones

(b) Changes in accessibility of Liège center

(c) Changes in accessibility of Liège Sart-Tilman

(d) Changes in accessibility of suburban Esneux

Figure 6. Profile for changes in average accessibility and accessibility of three representative zones according to scenarios

Table 1. The estimated coefficients of land use for arrivals from 6:00 to 9:00 AM

Dependent variable: number of arrivals			
Independent variable	coefficient	std.error	t value
Light industry	-0.003^{*}	0.002	-1.693
Heavy industry	0.001^{***}	0.0004	2.834
Commercial agricultural production	0.008^{***}	0.002	3.290
Energy production	0.003^{*}	0.001	1.952
Health and social action services	-0.107^{***}	0.035	-3.013
Education services	0.004^{***}	0.001	4.564
Rail transport	-0.009^{***}	0.003	-2.744
Other compatible residential uses at medium population density	0.001^{***}	0.0003	4.668
Other compatible residential uses with undefined housing density	0.073^{***}	0.003	27.449
Permanent residential use with undefined housing density	-0.035^{***}	0.008	-4.396
Permanent residential use with medium population density	0.018^{***}	0.003	6.009
Constant	-73.020	92.409	-0.790
Number of Observations	123		
R^2 / Adjusted R^2	0.907 / 0.898		
Residual Std. Error (df = 111)	624.158		
F Statistic (df = 11; 111)	98.199^{***}		

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

has the most inbound trips at 8:00 am. However, its dynamic accessibility is significantly affected by congestion from 9:00 to 11:00 am. In the afternoon, it is much less attractive than the morning peak, and the accessibility obviously declines. The suburban zone has distinct fluctuations of dynamic accessibility predominantly caused by congestion. In particular, at 8:00 am, the population concentration is relatively high but the dynamic accessibility drops due to outbound journeys for work. In the reference scenario, the accessibility value for the third zone (suburban) is substantially lower than the average value (7,540) and far below the central area (29,255).

4.3 Land use and accessibility

Table 1, Table A.3 and Table A.4 present the final regression results analyzing relationships between Level 3 LU classifications and mobile phone-derived arrivals across different time periods. The results reveal distinct LU types that exhibit statistically significant influence on arrival patterns at the cellular level, with varying impacts observed throughout the day.

In this research, attractiveness is found to have a predominant positive effect on dynamic accessibility. To filter out essential LU variables for mobile phone-based arrivals, we performed a stepwise regression based on the outcome of VIF analysis. From Table 1 to Table A.4, we see the influential LU changed in different time slots, including the variation in the significance of the same LU or the change of LU type, for instance, from education services in the morning to commercial services in the afternoon rush hours. Permanent residential use with medium population density represents residential areas where the number of inhabitants within a radius of 200 meters is between 250 and 499. Low population density is set as between 80 and 249. Other compatible residential uses with undefined housing density mean residential areas where other non-conflicting uses coexist where the number of inhabitants within a radius of 200 m is undefined. From Table 1, it is found that, on average, each additional permanent residential use with undefined housing density is associated with a decrease of 0.035 arrivals in the morning, assuming other independent variables are held constant, while in the afternoon, its effect is insignificant.

In addition, the other public services and sports infrastructures show a significant effect in the afternoon. It is noted that rail transport has a significant negative effect on the attractiveness of the destination, which is counterintuitive. One of the potential reasons is that the LU value approximated from the vector map is the area of a parcel with possible mixed uses instead of the number of railway stations. Nevertheless, with R^2 scores of 0.907 in the morning peak, 0.902 during off-peak, and 0.932 in the afternoon peak, we see an excellent goodness-of-fit of the regression model based on attraction mass and LU. The finding is helpful for researchers to calibrate the destination choice model better using influential LU variables across the day when facing a limit of travel demand data.

Similarly, we perform a stepwise regression for LU and the dynamic accessibility from the interplay of public transport travel time and attraction mass for two periods with rush hours (Table 2). Apart from agricultural infrastructure, other compatible residential uses at medium population density, and other compatible residential uses with undefined housing density, other LU variables described in the regression model for mobile phone-based trips have no significant influence on dynamic accessibility. Besides, the other residential use has a significant negative effect on accessibility. However, the goodness-of-fit is worse than the regression model between mobile phone-based arrivals and LU, which implies a more complicated relationship between LU and dynamic accessibility than destination attractiveness. Apart from attractiveness, the travel cost and the competition for opportunities demanded play a role in accessibility measures.

5. Conclusion and Future Research

Big data sources such as MPD offer new opportunities for the analysis of time-sensitive accessibility. The openly available GTFS makes it possible to derive dynamic travel time and reinforces the study of dynamic accessibility. This research utilizes mobile phone-based attractiveness and public transport travel time to explore spatial and temporal patterns of dynamic accessibility measures. Instead of using traditional LU examples, such as the static number of jobs as the opportunity variable, we approximated mobile phone-based arrivals as opportunities, as they are time-sensitive. Besides, the mobile phone-based

Table 2. The estimated coefficients of land use for dynamic accessibility

Dependent variable: Accessibility	**AM Peak (6:00 to 9:00 am)**		
Independent variable	coefficient	std.error	t value
Other residential uses	-0.304^{***}	0.056	-5.167
Agricultural infrastructure	0.179^{***}	0.057	3.137
Other compatible residential uses at medium population density	0.226^{***}	0.058	3.887
Other compatible residential uses with undefined housing density	0.519^{***}	0.058	8.909
Constant	0.000	0.055	0.000
Number of Observations	123		
R^2/Adjusted R^2	0.6328 / 0.6204		
Residual Std. Error (df = 118)	0.6161		
F Statistic (df = 4; 118)	50.84^{***}		
	PM Peak (15:00 to 18:00 pm)		
Other residential uses	-0.292^{***}	0.058	-5.007
Agricultural infrastructure	0.167^{***}	0.057	2.957
Other compatible residential uses at medium population density	0.225^{***}	0.058	3.892
Other compatible residential uses with undefined housing density	0.536^{***}	0.058	9.258
Constant	0.000	0.055	0.000
Number of Observations	123		
R^2/Adjusted R^2	0.6370/0.6247		
Residual Std. Error (df = 118)	0.6126		
F Statistic (df =4;118)	51.77^{***}		

Note: $^{**}p<0.05$; $^{***}p<0.01$

traffic analysis zones have relatively small spatial sizes (6.5 km squares on average of 123 zones), especially for the conurbation area. The impact of the public transport system changes progressively depending on the cut-off time considered, and the size of average accessibility gains could vary fourfold between the city center and suburban transport zones. If these results are incorporated into a cost-benefit analysis or multi-criteria analysis, important implications can be derived for informed decision-making.

Furthermore, the relationship between LU and accessibility is complex, and different conurbations around the world exhibit unique city characteristics. It is challenging to directly categorize patterns of dynamic accessibility based on types of LU and find a universal relation applied to different urban areas. Specifically, we see the significant impact of compatible residential use on destination attractiveness and location-based accessibility in the district of Liège, which implies the necessity of further exploring mixed LU effects.

In terms of limitations of this research, first, origins with lower scheduled access from schedule-based GTFS data tend to produce less reliable estimates and are therefore typically overestimated compared to what is realized in practice, for instance, from AVL data mentioned in Wessel and Farber (2019). Accordingly, they can report only the effects of planned change caused by public transport on accessibility, not what actually occurs. Second, MPD have its own bias and were determined by the data provider using an undisclosed algorithm based on population statistics and the most probable place of residence. The granularity of the data, while sufficient for identifying broad mobility patterns, limits more detailed behavioral interpretations. Finally, although validation of the observed mobility evolution was beyond the scope of this project, future studies could build on this foundation to conduct more comprehensive validations.

Consequently, we introduce the LU data from a web map portal to explain the relationship between LU and location-based accessibility. While this study offers valuable insights, certain considerations should be noted to inform future research. The LU value here refers to the area value of a parcel with possible mixed uses, which is not as intuitive as the opportunities explained by traditional data on various jobs or services. This gives us the future direction of integrating building-based land use data or points of interest to enhance the study of land use's effect on dynamic accessibility. Moreover, incorporating dynamic travel times across various transport modes to make accessibility scenarios more reflective of real-world conditions is a crucial step in the advancement of sophisticated accessibility-based travel models.

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Appendix

A. Additional Tables of Regression Results

Table A.3. The estimated coefficients of land use for arrivals from 11:00 to 14:00 PM

Dependent variable: number of arrivals			
Independent variable	coefficient	std.error	t value
Agriculture	0.012^{*}	0.006	1.864
Light industry	-0.004^{*}	0.002	-1.861
Commercial agricultural production	0.013^{***}	0.003	5.024
Health and social action services	-0.095^{**}	0.044	-2.181
Education services	0.003^{***}	0.001	3.244
Rail transport	-0.018^{***}	0.004	-4.351
Other compatible residential uses at medium population density	0.002^{***}	0.0004	4.612
Other compatible residential uses with undefined housing density	0.092^{***}	0.003	27.475
Permanent residential use with undefined housing density	-0.041^{***}	0.010	-4.058
Permanent residential use with medium population density	0.021^{***}	0.004	5.513
Constant	-54.883	126.858	-0.433
Number of Observations	123		
R^2/Adjusted R^2	0.902/0.893		
Residual Std. Error (df = 112)	782.053		
F Statistic(df = 10; 112)	103.180^{***}		

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table A.4. The estimated coefficients of land use for arrivals from 15:00 to 18:00 PM

Dependent variable: number of arrivals			
Independent variable	coefficient	std.error	t value
Other public services	0.001^{**}	0.0003	2.539
Heavy industry	0.001^{**}	0.0003	2.183
Agricultural infrastructure	-0.006^{**}	0.003	-2.253
Sports infrastructures	0.002^{**}	0.001	2.401
Commercial services	0.008^{***}	0.002	4.075
Electricity gas thermal energy distribution services	0.005^{*}	0.003	1.722
Health and social action services	-0.096^{***}	0.031	-3.819
Rail transport	-0.011^{***}	0.003	7.455
Other compatible residential uses at medium population density	0.002^{***}	0.0002	29.522
Other compatible residential uses with undefined housing density	0.068^{***}	0.002	4.483
Permanent residential use with medium population density	0.012^{***}	0.003	1.803
Permanent residential use with low population density	0.004^{*}	0.002	2.438
Aquatic natural areas	0.001^{**}	0.0003	-0.433
Constant	44.745	92.586	0.483
Number of Observations	123		
R^2/Adjusted R^2	0.932/0.924		
Residual Std. Error(df = 109)	556.394		
F Statistic (df = 13; 109)	115.321^{***}		

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$