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Transport and Telecommunication, 2025, volume 26, no. 1, 82-89
Transport and Telecommunication Institute, Lauvas 2, Riga, LV-1019, Latvia
DOI 10.2478/ttj-2025-0008

ENHANCING PUBLIC TRANSPORT ACCESSIBILITY FOR PEOPLE WITH MOTOR DISABILITIES THROUGH DEEP LEARNING ON GRAPHS

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Globally, over a billion people live with disabilities, facing significant challenges in accessing public transport, which impacts their autonomy, social participation, and economic status. Current research indicates that common problems include inadequate service in terms of destination, timing, and travel duration, as well as physical barriers at stops and the behaviour and proficiency of transit staff. These issues are exacerbated for those with visual impairments or mobility challenges, such as wheelchair users, who face even greater obstacles. This research emphasizes the necessity of an “enabling transport” environment that considers all aspects of travel for those with limited mobility. This includes the physical layout of pedestrian routes, the design of buildings, and the functionality of public transportation systems. Practical measures like aligning bus floors with pavements, as mandated in the European Union, and optimizing the deployment of accessibility equipment like pallets are discussed as essential for improving access. The authors propose a research methodology that employs a graph-based approach in combination with recurrent neural networks models to suggest most accessible pathways considering fleet availability, vehicle capacity and road quality of sidewalks. The approach includes a comprehensive case study in Riga, Latvia, utilizing data from local transport operators and crowdsourced information to assess and address physical barriers. This innovative application of deep learning on graphs aims to significantly improve the inclusivity and efficiency of public transport for people with disabilities. The study emphasizes the broader benefits of creating accessible environments that improve usability for all citizens, not just those with disabilities.

Keywords: MaaS, wheelchair users, inclusivity, mobility data, graph theory, recurrent neural networks

1. Introduction

Social inclusion seeks to improve the conditions and opportunities of disadvantaged people based on factors such as age, gender, disability, ethnicity, religion, or socioeconomic status. It entails increasing their social participation by providing better access to resources, opportunities, and respect for their fundamental rights (Atkinson & Marlier, 2017). People with mobility impairments face unique safety and accessibility challenges in major cities. According to Zahabi *et al*. (2023), Mobility-as-a-Service (MaaS) systems should include design guidelines for real-time user location, continuous instructions, adaptability, reverse route support, live help, clear system instructions, and user feedback.

Individuals with disabilities frequently face significant accessibility challenges, particularly on public transportation, as extensively documented (O'Neill, 2021; Bezyak & Sabella, 2017). Services frequently fail to meet their needs, with inaccessible pathways and stations reducing autonomy and socioeconomic status. Physical barriers, such as inadequate ramps and restrooms, pose significant obstacles for wheelchair users (Evcil, 2018). Participation in activities is limited by social, organizational, and attitudinal barriers, including discriminatory behaviours and inadequate communication infrastructure (Bridger & Evans, 2020). Technological barriers also limit accessibility, emphasizing the need for infrastructure designed for people with disabilities (Kamyabi & Alipour, 2018). Effective strategies include providing adequate transportation and professional services. Despite these efforts, many wheelchair users continue to rely on private vehicles due to limited public transportation.

Addressing these barriers necessitates both physical adaptations and efforts to change societal attitudes toward disability by encouraging social inclusion and technological support (Deganis *et al.*, 2021). Accessible design principles for users with motor disabilities should consider their unique challenges. Customizable user profiles enable personalized route planning; interactions should be designed with simple gestures; caregivers should be able to easily access updates in the proposed routes; and ultimately the design of the system should minimize physical exertion while remaining accessible to users with varying motor abilities (Harriehausen-Muhlbauer, 2016).

Despite advancements in navigation systems, a human-centric approach that takes individual constraints and preferences (e.g., points of interest, historical trips) is required. Understanding mobility behaviours is critical to improving public transportation (PT) systems. Over the last two decades, researchers such as Kim *et al.* (2021) and Welch & Widita (2019) have used PT smart card data to conduct spatiotemporal analyses of urban mobility patterns. The initial analyses look at the spatial distribution and dynamics of PT boarding over time. Zhong *et al.* (2017) examined boarding numbers and temporal patterns, whereas Briand *et al.* (2017) and Mohamed *et al.* (2016) clustered passengers and studied their behaviour. However, boarding data alone does not reveal all mobility trajectories, necessitating the estimation of trip destinations. Tao's (2021) trip chain analysis demonstrates techniques for distinguishing final destinations using algorithms and time thresholds. Briand *et al.* (2017) used clustering techniques to examine demand regularity, whereas Goulet-Langlois *et al.* (2017) associated travel patterns with socio-demographic characteristics. Long & Thill (2015) and Qi *et al.* (2019) are two recent studies that combined smart card data with other sources to conduct comprehensive mobility analyses. For OD matrix estimation, common methods treat origin-destination trips as vectors grouped by Traffic Analysis Zones (TAZ), as demonstrated by Kumar *et al.* (2021). Xu *et al.* (2021) proposed a more data-driven approach, clustering POI for zone definition.

Deep Learning applications have not been extensively studied for wheelchair user accessibility. This study examines a case study in Riga, Latvia, where graph-based approach and Recurrent Neural Networks (RNN) models (Yu, 2019) are used to identify accessible routes while considering transportation availability and sidewalk conditions. These models optimize loss functions representing accessibility predictions, and performance is measured using metrics such as mean squared error (MSE).

Finally, this study employs advanced neural network techniques to improve urban public transportation accessibility for wheelchair users. This approach aims to improve the efficiency, inclusivity, and personalization of public transportation by integrating multiple data sources.

2. Case study formulation

Inadequate sidewalk infrastructure, poorly designed public transport facilities, and a general lack of real-time assistance exacerbate the difficulties of daily commutes. Such barriers prevent access to essential services and limit participation in community life and urban environments. The present case study based on Riga Public Transportation network and sidewalk infrastructure, illustrates how the integration of several data sources – such as GTFS static data, electronic ticket registration data, obtained from *Riga Satiksme* (local transport operator), and crowdsourced sidewalk data from OpenStreetMap – can enhance public transport accessibility, making daily travel within an urban setting far more manageable for individuals with mobility challenges. For simplicity and clarity, this practical case study presents a simulated trip of a 20-year-old wheelchair user who needs to travel from the hospital to the university, arriving no later than 10:30 AM.

The *public transit data* from Riga Satiksme (Rīgas Satiksme, 2024) adheres to the *General Transit Feed Specification* (GTFS) standard and is essential for mapping accessible public transport routes and schedules. This analysis provides crucial information for individuals with disabilities, enabling them to plan their travel using routes with fewer changes and shorter walking distances. The dataset includes several key files: the agency file contains details about the transit agency, such as name, URL, contact information, time zone, and language; the routes file details each route with identifiers, names, descriptions, transport type, URLs, and visual identifiers like colour codes; the trips file links routes to specific trips, including trip identifiers, route identifiers, service IDs, trip directions, and physical line details. Additionally, the stop times file specifies arrival and departure times at each stop for every trip, while the stops file lists all stop with unique identifiers, names, descriptions, coordinates, and metadata about stop types and hierarchical relationships. The calendar file includes service schedules, availability by day, and exceptions like holidays or events, and the shapes file provides geospatial data for mapping vehicle paths along routes. The attributions file credits data providers and associated organizations. For wheelchair users, accessibility flags indicate whether routes and stops are suitable for wheelchair access, aiding in journey planning.

The *electronic ticket registration* dataset (Rīgas Satiksme, 2024) captures every ticket validation, providing insights into passenger flow and ticket usage. This dataset includes the timestamp of ticket validation, a unique validation ID for each event, the card type indicating the type of ticket or pass used, the vehicle ID where the validation occurred, the route number linking validation to a specific route, and the stop ID identifying the stop where the ticket was validated.

Ultimately *OpenStreetMap* (OpenStreepMap, 2024) offers detailed information about pedestrian pathways, including sidewalk widths, surfaces, and the availability of curb cuts and ramps. This data is crucial for assessing pedestrian accessibility and ensuring safe and reliable navigation through the city. Paths are defined by sequences of nodes and characterized by tags detailing their physical attributes like surface type, quality, and lighting conditions.

3. Modelling an accessible transportation network

Urban transportation networks must be inclusive to provide all citizens with equal opportunities to participate in social, economic, and cultural activities. For individuals with motor disabilities, this inclusivity hinges on accessible infrastructure and public transport systems. Modelling an accessible transportation network requires a multi-layered approach, accounting for both physical infrastructure and dynamic variables such as passenger counts on transit routes. This section provides a detailed account of how we model an accessible network, focusing on sidewalk walkability, public transport integration, and the use of deep learning models to enhance accessibility predictions.

3.1. Assessment of sidewalk walkability

Sidewalks form the foundation of urban mobility, serving as the connection between homes, workplaces, and transport systems. Their condition and accessibility directly impact the ease with which people — particularly those with mobility impairments — can navigate the city. To quantify sidewalk accessibility, we introduce a **walkability score** based on three key parameters: surface type, smoothness, and lighting.

- **Surface type** (X_1): This parameter quantifies the material and structural quality of the sidewalk surface. It is rated on a scale from 1 to 5, where 5 corresponds to highly stable, wheelchair-friendly surfaces like asphalt or concrete, and 1 corresponds to more challenging surfaces like gravel or dirt.
- **Smoothness** (X_2): It measures the evenness and continuity of the sidewalk. Smooth, uninterrupted paths are essential for easy navigation by wheelchair users. Like surface type, it is rated from 1 to 5, with higher values assigned to sidewalks that offer better manoeuvrability.
- **Lightness** (X_3): It is a binary parameter (1 or 0) that assesses whether the sidewalk is adequately lit. Well-lit sidewalks improve both the safety and comfort of users, especially during night-time or in poorly lit areas.

Then, walkability score, A_s, is calculated using the following weighted average formula:

$$A_s = \sum_{i\in X} \alpha_i x_i \,/\, \sum_{i\in X} \alpha_i, \tag{1}$$

where $X \subseteq \{X_1, X_2, X_3\}$ is the set of available parameters, x_i is the score is the score assigned to each parameter i and α_i is the weight assigned to each parameter i. Weights can be adjusted based on specific priorities or local conditions. For instance, if smoothness is particularly important due to frequent rain, it can be assigned a higher weight.

After calculating A_s, the resulting scores are categorized into five walkability levels: *inaccessible* ($A_s < 1.5$); *poor accessibility* ($1.5 \le A_s \le 2.5$); *moderately accessible* ($2.5 \le A_s \le 3.5$); *accessible* ($3.5 \le A_s \le 4.5$); and lastly, *highly accessible* ($A_s \ge 4.5$). This scoring system not only allows us to visualize sidewalk accessibility across a city, highlighting the areas where infrastructure improvements are needed most urgently, but can also provide users with a real view of accessibility challenges in the local pedestrian network.

3.2. Integration of public transport data

While accessible sidewalks are crucial, individuals with mobility impairments also rely heavily on accessible public transport systems to navigate the city. In this section, we develop a pipeline to integrate public transport data, enabling us to identify the most accessible routes and stops.

The public transport data, provided by the Riga public transit agency, adheres to the General Transit Feed Specification (GTFS). It includes several key datasets such as routes, trips, stops, and stop times. The first step in our analysis involves calculating the geodesic distance between key Points of Interest (POIs) (e.g., hospital, university) and transit stops. This ensures that all stops within a reasonable walking distance (e.g., 250 meters) are considered accessible.

We focus on trolleybus routes in our case study since they are typically more accessible for wheelchair users. Using the GTFS data, routes are filtered based on the '*route_type*' variable, which in this context encodes trolleybus routes as *800*. Temporal adjustments are made to trips that exceed 24 hours, allowing for the accurate identification of trips within specific time windows (e.g., from 08:00 to 10:30 AM).

To efficiently model the public transport network, we use a **directed graph** representation. A directed graph $G = (V, E)$ is an ideal structure for modeling transportation systems, where $V$is represents the set of vertices (stops) and E represents the set of edges (routes between stops). Each stop is represented as a node in the graph, with relevant attributes such as the stop name, latitude, and longitude. If the stop is not the first in the sequence, an edge is added between the current stop and the previous one. Each edge contains attributes such as the **route identifier** (e.g., 'riga_trol_3' or 'riga_trol_15'), the **departure time** from the stop, and the **arrival time** at the next stop.

The formal representation of an edge $e_{i\to j}$ between two consecutive stops v_i and v_j is:

$$e_{i\to j} = (v_i, v_j, r, t_d, t_a, \Delta t), \tag{2}$$

where v_i, v_j are the consecutive stops, r is the route identifier, t_d is the departure time from stop v_i, t_a is the arrival time at stop v_j, and Δt is the travel time between v_i and v_j.

If a **direct route** doesn't exist, **transfer hubs** – stops where multiple routes intersect – are identified using graph theory metrics. A transfer hub $h \in V$ is defined based on one or more of the following criteria:

- **High degree**: $deg(h)$ is significantly higher than the average, meaning more routes connect at this stop.
- **Route intersections**: Multiple distinct routes pass through h.
- **Centrality**: h has a high ***betweenness centrality***, meaning it lies on many shortest paths within the transport network.

Transfer hubs are crucial for ensuring that users can switch between accessible routes with minimal difficulty. To conclude, by implementing this graph representation, the transport network can be efficiently analysed and optimized, ensuring that individuals with mobility impairments have access to the most effective and accessible transportation options.

3.3. Prediction of passenger count

While static infrastructure and transit data are vital for modeling an accessible transportation network, real-time and predictive data, such as passenger counts, are critical in ensuring that wheelchair users can navigate public transport at a given time. Crowded buses, even if physically accessible, may be difficult to use for wheelchair users. To address this, we employ **Recurrent Neural Networks (RNNs),** namely Long Short-Term Memory (LSTM) and Gated Recurrent Unit (GRU), to predict passenger loads and integrate these predictions into our graph-based model.

Passenger counts are aggregated over defined **time windows** (e.g., every 10 minutes) to form a continuous time series for each route. The total passenger count $X_{\Delta t}(n)$ for time window n is calculated as:

$$X_{\Delta t}(n) = \sum_{t\in[t_n, t_{n+1})} X(t), \tag{3}$$

where where t_n and t_{n+1} are the start and end times of the n-th time window.

To capture temporal dependencies, we create **lagged features**, representing the passenger counts from previous time steps. The lag of previous steps τ for time window n is defined as $L(n) = X_{\Delta t}(n - \tau)$.

Hence, the feature vector for time step n becomes:

$$X_n = (X_{\Delta t}(n), X_{\Delta t}(n-1), X_{\Delta t}(n-2), \dots, X_{\Delta t}(n-\tau))^T. \tag{4}$$

Ultimately, the passenger count data is normalized using **min-max scaling**. This normalized data is used as input for the two types of RNNs. Both models are trained to predict future passenger loads based on electronic ticket registration data. The models are compiled using the Adam *optimizer* and **Mean Absolute Error (MAE)** as the *loss function*. Training is conducted on the training dataset for 20 *epochs* with a *batch size* of 32, and 20% of the training data is used for *validation*. After training process, the models can predict passenger counts on the test dataset. An **Exponential Moving Average (EMA)** method is also implemented as a baseline for comparison. Performance metrics, including MAE, **Mean Squared Error (MSE)**, and **Root Mean Squared Error (RMSE)**, are calculated for each model to evaluate their prediction accuracy.

For each stop v_i, the predicted passenger count $\hat{X}(v_i)$ is added as a node attribute. This ensures that each node (stop) has an associated predicted passenger count. Edges are then marked as *wheelchair accessible* based on the predicted passenger counts. If the passenger count on a route is below a specified threshold δ (e.g., according to experts' estimation is 50% of fleet passenger load), the edge is marked as wheelchair accessible. This criterion assumes that routes with lower passenger volumes are easier for wheelchair users to navigate.

4. Case study results

The first part of the analysis involves evaluating the accessibility of sidewalk infrastructure across Riga (Figure 1). The sidewalk segments are color-coded to represent different levels of accessibility, with red indicating the lowest accessibility and green indicating the highest, based on walkability score formulated in (3.1). Most of the sidewalks in the central areas of Riga are marked in red, suggesting poor conditions for wheelchair users and individuals with mobility challenges. Conversely, certain segments, particularly in parks and newly developed areas, are marked in green, indicating optimal accessibility. Detailed attributes for each sidewalk segment, such as surface type, smoothness, and lighting conditions, provide insights into the specific characteristics affecting accessibility. For example, a segment marked "*Surface: Paving_stones, Smoothness: Average, Lighting: Lit*" indicates a well-maintained, well-lit segment conducive to easy navigation.

Moreover, the integration public transport routes provide a holistic view of how these two crucial aspects of urban mobility interact. Public transport routes are highlighted using blue and purple lines, with stops marked by information icons indicating additional details available at these points. This integrated view reveals that sidewalks around central transport stops are predominantly marked in red, indicating poor accessibility. This poses significant challenges for individuals with mobility issues when transitioning from transport stops to sidewalks. Key stops and transfer points in central locations and major intersections, are particularly highlighted. These areas are critical for ensuring smooth transitions and must be prioritized for accessibility improvements.

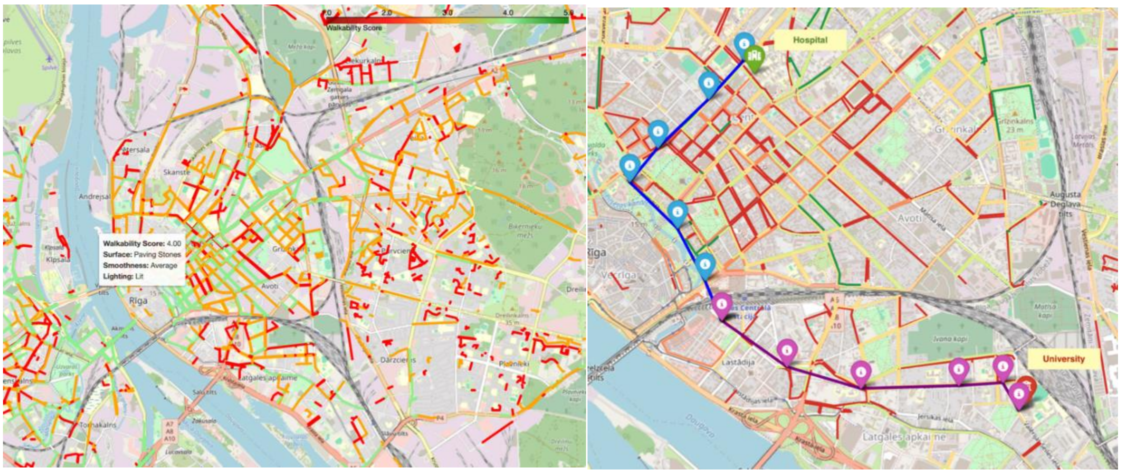

Figure 1. Assessment of sidewalk accessibility (left) and integration of optimal public transport routes from hospital to university (right)

The next phase of the analysis focuses on predictive modelling of passenger counts for the calculated trip segment, according to method formulated in (3.2), include two suggested routes: Trolleybus 3 and Trolleybus 15 (Figure 2). Both time series displays the actual passenger counts alongside predictions from the LSTM, GRU, and EMA models. The predictions closely follow the actual passenger counts, although there are some discrepancies. Surprisingly, the moving average method again provides a slight superior accuracy with a significantly lower MAE, MSE and RMS, compared to the Deep Learning models. The table below compares the benchmark results for the models across the two routes, summarising the accuracy values obtained for each model and route combination.

Although the EMA model consistently shows increased performance with lower MAE, MSE, and RMSE values for both routes, The LSTM and GRU models have comparable performance (Table 1) and this suggest that, despite the advanced capabilities of LSTM and GRU models in capturing temporal dependencies, the simpler EMA model is more effective for this specific passenger count prediction task, likely due to its ability to smooth out short-term fluctuations and capture the overall trend.

Finally, the enhanced graph (Figure 3) showcases a detailed visualization of a public transport network with predictions on passenger counts and indications of wheelchair accessibility. Each node in the graph represents a stop in the public transport network and includes labels with the stop name, predicted passenger count, departure time, and arrival time. The edges connecting these nodes represent the route segments between the stops and are labeled with the route number and the wheelchair accessibility status. The predicted passenger counts are derived from LSTM model predictions and are critical in determining the wheelchair accessibility status of the routes. Lower passenger counts facilitate easier navigation for wheelchair users. The data shows a range of predicted counts, with several stops well below the 40-passenger threshold, reinforcing the accessibility of these routes. Notably, "Mazā Kalna iela" and "Katoļu iela" have higher passenger counts but still maintain accessibility status, possibly due to sufficient infrastructure to handle higher passenger volume.

Table 1. Benchmark comparing models' performance along trolleybus routes

Model	Tr 3/MAE	Tr 3/MSE	Tr 3/RMSE	Tr 15/MAE	Tr 15/MSE	Tr 15/RMSE
LSTM	6,5606	124,0955	11,1398	13,0864	360,5079	18,987
GRU	6,5603	124,0044	11,1357	13,4695	363,8071	19,0737
EMA	**4,7719**	62,981	7,936	**9,4632**	189,956	13,7825

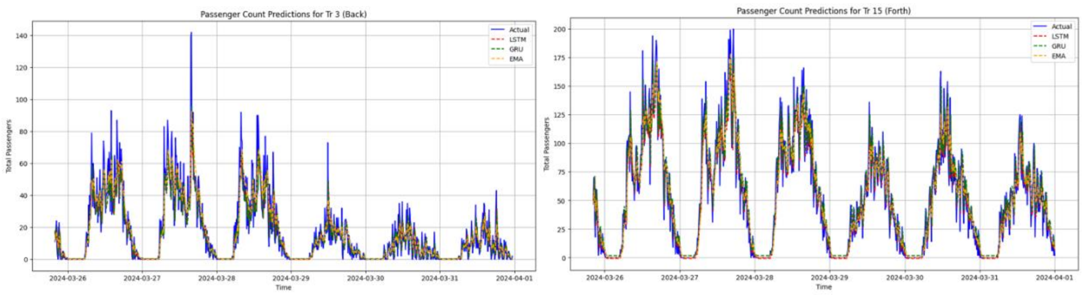

Figure 2. Comparison of LSTM, GRU predictions for Trolleybus 3/Trolleybus 15 (including baseline)

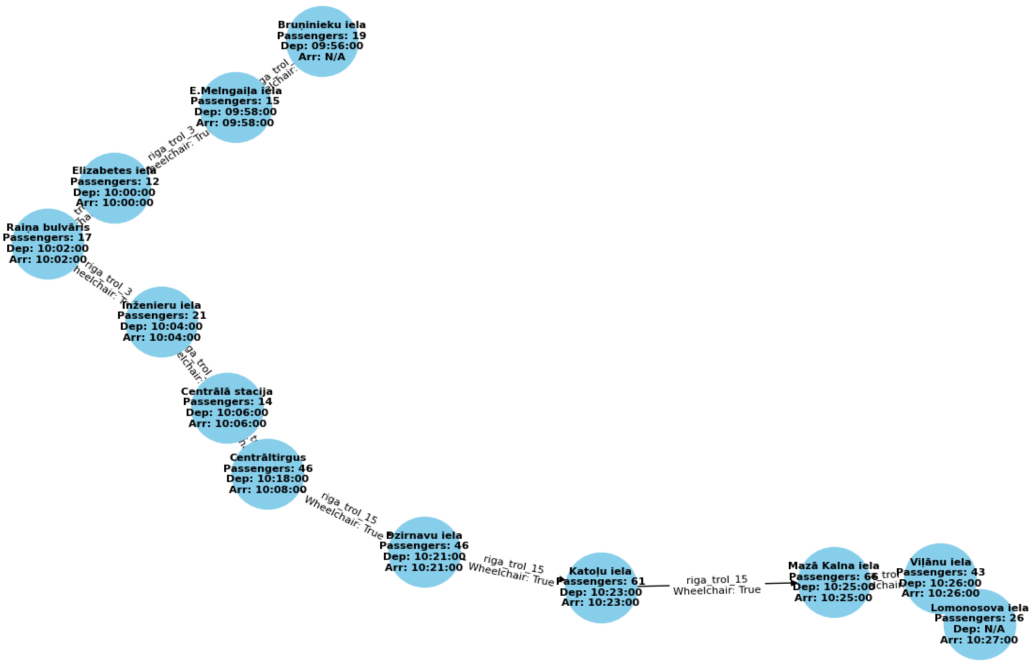

Figure 3. Trip segment (hospital to university) representation combining public transport accessible route and LSTM predictions

5. Discussion and conclusion

This research has the potential to enhances the accessibility of Riga's public transportation and sidewalk infrastructure for individuals with motor disabilities by integrating various data sources. The assessment of sidewalk infrastructure revealed substantial variability in accessibility, with central areas generally in poorer condition compared to newly developed areas and parks. The integration of public transport data into a directed graph facilitated efficient route optimization, identifying the most accessible routes and transfer hubs for wheelchair users. Predictive modelling using deep learning models and the EMA method provided valuable insights into passenger counts, with the simpler EMA model outperforming the more complex models in this specific context. The enhanced graph, incorporating predicted passenger counts, allowed for a dynamic assessment of route accessibility, making it easier for wheelchair users to plan their journeys.

This study has important implications for improving MaaS demand of vulnerable users, personalizing public transport services, highlighting critical areas needing infrastructure improvements and providing insights for optimizing routes and schedules. The methodology can serve as a model for other cities aiming to enhance accessibility for people with disabilities, offering a framework for real-time accessibility assessments using advanced predictive models and real-time data sources.

However, several limitations must be acknowledged, particularly the issue of incomplete data and inconsistency from data providers. The accuracy of GTFS data relies on the completeness and timeliness of updates from the transit agency. Any discrepancies or delays in data updates can significantly affect route planning accuracy. Additionally, the crowdsourced data from OpenStreetMap may have inconsistencies in quality and coverage, leading to potential gaps in accessibility information. Despite these limitations, the research provides a robust framework for improving urban mobility for individuals with motor disabilities. Future studies should focus on incorporating additional data sources and exploring Graph Neural Networks to further enhance the model's applicability and effectiveness in creating more inclusive urban environments.

Acknowledgements

This research in the frame of project DCODE has received funding from the European Union's Horizon 2020 Research and Innovation Programme under the Marie Skłodowska–Curie grant agreement No 955990.

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