Case Studies on Transport Policy 21 (2025) 101545

Contents lists available at ScienceDirect

Case Studies on Transport Policy

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

# Measuring the integration of micromobility and public transport – the development of a new network analysis tool

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ARTICLE INFO

*Keywords:*
Micromobility
Last-mile
Multimodality
Public transport
Accessibility
GIS analysis
Sustainable urban mobility

ABSTRACT

The integration of micromobility and public transport is an increasingly relevant and desirable strategy to promote more sustainable alternatives to private car travel. For it to be successful, however, adequate infrastructure to facilitate intermodal trips needs to be provided, at stops and in the catchment areas surrounding them. In this study, a methodology is proposed to holistically assess the quality and availability of such infrastructure using Open Data. The proposed methodology combines a network analysis of the catchment areas with an assessment of the public transport stops. The assessment results in an index that objectively quantifies the quality and availability of infrastructure that is necessary for a successful integration of micromobility and public transport. The methodology has been applied to the case study of the light rail network in Dublin, Ireland, showing that the index is a straightforward combination of datasets which allows to compare public transport stops in terms of their suitability for the integrated use of micromobility and public transport. Overall, the methodology is a valuable assessment tool to objectively determine the integration of micromobility and public transport, applicable in any geographical context – for which the required open datasets are available – and to inform decision-making processes relating to improving the accessibility of public transport services.

## 1. Introduction

To fully harness the potential of micromobility – a term generally used to indicate private and shared bicycles, e-bikes, and e-scooters – in creating more sustainable and connected cities, its integration with existing public transport systems is crucial in providing attractive alternatives to private motorised vehicles for longer distance journeys. The integration, however, can only be successful in areas where the built environment at and around public transport stops is conducive to the combined use of these modes. Unlike conventional first/last mile or feeder modes such as walking or buses, electric micromobility – including e-bikes and e-scooters – offer flexible access/egress alternatives for short distances. This paper addresses the growing need to evaluate infrastructure integration that supports such modes when linked with conventional public transport. Well-designed infrastructure for micromobility use around public transport stops and stations has the potential to increase the spatial reach and accessibility of existing public transport services while also reducing emissions and energy use per passenger-kilometre (ITF, 2020). The interactions between micromobility and public transport have been analysed from a number of different perspectives. Accessibility analyses, for example, have studied the level of access and spatial reach of public transport services using different modes, for example by determining the number of jobs that can be reached from a given point along a public transport service within a given time. Catchment area analyses, on the other hand, have focused on analysing access and egress to and from opportunities around specific public transport stops, mainly using Euclidean distances. A number of studies have also developed assessment strategies for cycling infrastructure, such as bicycle level of service or bikeability indices to categorise the quality of existing infrastructure. However, while these analyses all contribute to a better understanding of the individual components of such a complex system, a holistic and system-based approach is required to fully and objectively assess the integration of micromobility and public transport. Such an assessment strategy has, to date and to the best of the authors' knowledge, not yet been developed.

The methodology, presented in this paper, is an effective tool that can be used by planners, policymakers and services providers to objectively assess, combine and visualise an array of complex datasets and

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https://doi.org/10.1016/j.cstp.2025.101545
Received 23 April 2025; Received in revised form 10 July 2025; Accepted 10 July 2025
Available online 13 July 2025

information to facilitate decision-making processes related to infrastructure improvement and implementation aimed at promoting the combined use of micromobility – the term is used here to indicate private and shared bicycles and e-scooters – and public transport. The tool could also be developed further for specific applications or used in combination with other data to identify the stops that are most suitable for the deployment of infrastructure or micromobility sharing services. The novelty and effectiveness of the methodology provides a significant contribution by facilitating the assessment of infrastructure availability and quality to promote the integrated use of micromobility and public transport. The remainder of the paper is structured as follows: in Section 2 the relevant literature is reviewed in a number of thematic subgroups; Section 3 delineates the methodology and case study area; Section 4 outlines the results; in Section 5 the results are discussed and contextualised, with a remark on the limitations and recommendations for future research, while Section 6 presents the conclusions.

## 2. Literature review

### 2.1. Bikeability indices and factors that influence micromobility use

While cycling as a transport mode has been studied in greater detail, including user preference and infrastructure quality requirements, the more recent introduction of microvehicles has yet to be fully analysed. However, given that in most countries new microvehicles are generally used on cycling infrastructure, where available, and given the similar safety concerns and requirements of micromobility users, the cycling infrastructure is presumed to be also used by micromobility users. Therefore, it is assumed that the better the cycling infrastructure, the better the experience for micromobility users in general. The concept of developing assessment tools to determine the quality of cycling infrastructure in urban areas has been at the centre of several studies to date. The most common assessment metrics in the literature are the Bicycle Level of Service (BLOS) and Bikeability Indices (Arellana et al., 2020). All studies conducted to date, in one form or another, focus on evaluating the availability and quality of cycling infrastructure in a given area based on a set of factors that are used to quantify and assess safety, comfort, and convenience for cyclists. Ahmed et al. (2024) conducted a systematic review of bikeability indices and found that while safety and comfort are commonly included, principles like coherence are often neglected, and suggesting that there is a need for more comprehensive indices. These tools and indices are usually centred on the five cycling infrastructure design principles: cohesion, directness, attractiveness, safety, and comfort (CROW, 2007; NTA, 2023). Arellana et al. (2020) provide a comprehensive systematic review of the peer-reviewed literature published between 1994 and 2020 on the development and use of bikeability indices and the indicators used in each study. The majority of studies (89 % of the 53 total studies reviewed) included factors relating to traffic safety, such as cycling infrastructure availability and type, and used microscale data to assess bikeability, focusing on the infrastructure available at the individual road segment or intersection level.

In a study conducted in the Netherlands an index was developed to assess bikeability in a transit-oriented development (TOD) context (Hartanto, 2017). In the analysis, a bikeability index was developed with a particular focus on the integration of cycling and long-distance train journeys. Factors such as the availability of bicycle parking at train stations were included in the index, as well as infrastructure quality, topography and directness of routes. This analysis, however, was limited to assessing the bikeability of the road segments within the catchment areas, without considering the actual routes from the origin points to the train stations. Werner et al. (2024) propose a model to estimate segment-based bikeability using open data, assessing its suitability through expert workshops and surveys, which confirmed the feasibility of data-driven modelling for segment-based bikeability assessments, thereby enabling urban and transport planners to identify and prioritise infrastructure improvements.

### 2.2. Catchment area analysis of public transport stops and stations

Studies show that railway stations with high-frequency, long-distance services are characterised by substantially larger catchment areas compared to light rail or bus stops (Gao, et al., 2024; Hochmair, 2015; Martens, 2004; Midenet et al., 2018). Gao et al. (2024) proposed a novel method that incorporates multi-modal access options and considers the door-to-door journey. The study found that acceptable access distances differ significantly by travel mode and are influenced by the main suburban rail journey. Bicycle and bus catchment areas extend further than those for urban rail transit, with their attractiveness rising initially before declining with distance. Walking is the most common access mode to public transport and the most analysed in the context of accessibility to public transport assessments or studies (Midenet et al., 2018). Access by walking, however, is severely restricted by distance – Hochmair (2015) found that walking is the predominant mode of access within 800 m of public transport stops (76 % walking access), it goes down to 55 % for distances between 800 m and 1.5 km and for distances greater than 1.5 km the bus becomes the predominant feeder mode. However, public transport feeder services can be restrictive due to low frequencies, route layouts and low traveling speeds due to adverse traffic conditions. Using micromobility as access mode, on the other hand, provides an opportunity to overcome these restrictions by providing a fast and convenient alternative to buses, and with a greater spatial reach than walking (Kager et al., 2016; Li et al., 2020). Zheng and Austwick (2023) applied a node (transport connectivity and access) – place (land use characterstics and urban form) model to classify station areas in Greater Manchester, and found that a balanced integration of transport functions and land-use planning is crucial for enchancing the effectiveness and sustainability of public transport systems. In countries with a high cycling modal share such as The Netherlands and China, there have been studies focusing on the use of bicycles for access and egress trips to and from public transport, but for most countries data availability is scarce (Martens, 2004).

### 2.3. Contribution and relevance of this study

The methodology developed in this study builds upon the findings from the existing literature to propose a novel evaluation of the connectivity and accessibility of suitable infrastructure for micromobility use in access and egress trips to and from public transport stops.

The main contribution of this paper is twofold: i) a methodology was developed to assess catchment areas of public transport stops based on a network analysis and optimal route selection for micromobility use via a time optimisation algorithm, where the quality and comfort of the infrastructure available is expressed by means of varying cycling/scooting speeds; ii) an index is proposed that allows to rank and compare different stops based on their attractiveness and accessibility for micromobility users.

The Micromobility and Public Transport Integration (MPTI) index, developed by this research, goes beyond the existing bikeability indices in that it combines indicators relating to the road network in the catchment areas of public transport stops with indicators that pertain to the stop itself such as, among others, the accessibility of the stop or the type and capacity of bicycle parking available. While most indices developed so far were used to quantify and determine bikeability at the road segment level to identify areas that are bicycle-friendly, the index developed in this study uses a time optimisation algorithm to determine the fastest paths to public transport stops from all surrounding origin points (OPs) based on the availability and quality of infrastructure. Using this methodology essentially allows to trace the routes with the best infrastructure from each origin point to the destination it is best connected with. The integration of micromobility and public transport is seen as an efficient and sustainable way of improving spatial reach and public transport ridership (Kager et al., 2016; Kosmidis and Müller-Eie, 2023).

## 3. Methodology

The methodology is presented in three sections: in the first section, the methodology to determine the catchment areas using a time optimisation algorithm is presented, followed by the second section, which introduces the MPTI index and includes a detailed description of the network analysis and stop analysis components. In the last section the case study area is presented.

### 3.1. Catchment area analysis

#### 3.1.1. Assigning varying cycling speed to model infrastructure quality and comfort

Micromobility riders tend to choose longer and less direct routes in order to use better infrastructure. This can be modelled by assigning higher cycling speeds to infrastructure that is more comfortable and more safe. Route choice is conducted using a time optimization algorithm to minimize travel time to approximate choosing a route with better infrastructure.

The underlying assumption that cyclists or e-scooter users choose longer routes with better infrastructure relies on a number of well-established findings from the existing literature:

(i) Perceived and actual cycling infrastructure quality and safety are proportional to the degree of separation from motorised traffic and adjacent motorised traffic speeds;
(ii) Infrastructure quality, comfort and safety are relevant factors in determining cycling route choice;
(iii) While direct routes are desirable, cyclists are likely to accept detours and therefore longer routes to cycle on better infrastructure.

The user preference of cyclists for low traffic and segregated infrastructure is well documented in the literature: Caulfield et al. (2012) found that, in Dublin, cycling routes with 'no infrastructure' or 'bus lanes' were the least favoured among all types of cyclists, with experienced users being more travel time sensitive than more vulnerable users. Hardinghaus and Weschke (2022) analysed cycling infrastructure preferences of different user groups in Berlin and found that there are no fundamental differences in what makes cycling infrastructure attractive to the different groups: all users benefit from an improvement in cycling infrastructure and lower motorised traffic volumes and maximum speeds. Such improving measures are particularly relevant for vulnerable user groups that have higher safety concerns. Kosmidis and Müller-Eie (2023) conducted a systematic literature review of bike-and-ride studies and found that the quality of cycling infrastructure and the traffic conditions around public transport stops had a significant effect on the decision to access a station by bicycle. Lin and Wei (2018) found that the presence of segregated cycling infrastructure is positively correlated with cycling speeds while increased motorised traffic results in longer cycling journey times. Zhang et al. (2021) found that also e-scooter users were willing to travel longer distances to use segregated cycling infrastructure and roads with lower motorised traffic volumes and maximum speeds.

The 'Cycling Design Manual' of the Irish National Transport Authority (NTA, 2023) describes the various types of cycling infrastructure in detail, as well as their suitability for different environments and adjacent traffic conditions. The definitions and suitability indications were used as a reference in this analysis to determine the infrastructure types available and the corresponding assigned cycling speeds (see Appendix A).

The commonly available routing algorithms are mainly based on two optimisation problems: distance optimisation to determine the shortest path, and time optimisation, to determine the fastest route. When trying to determine an optimal route based on other criteria, as is the case in this analysis – where infrastructure quality, comfort and safety are considered – there are two possible ways of modelling the different quality levels for individual segments. If using a distance optimisation algorithm, the length of each segment is multiplied by a weight factor, based on the assumption that when cycling on good infrastructure the actual distance is perceived to be shorter (weight factor $<1$) and when cycling on bad infrastructure or in dangerous conditions, the actual distance of the segment is perceived to be longer (weight factor $>1$). This methodology was used for example by Grigore et al. (2019) to determine bikeability in Basel. On the other hand, when using a time optimisation algorithm, varying cycling speeds are assigned to segments based on the quality, comfort and safety of the infrastructure to determine the optimal route – which is the methodology proposed in this analysis. The cycling speeds assigned in the model are not a reflection of actual or empirical speeds, they are simply a way of quantifying the users' preference for safer and more comfortable routes. Therefore, the routes that are determined by the time optimisation algorithm are not actually the fastest routes in reality, but the optimal routes based on infrastructure quality and safety.

#### 3.1.2. Network analysis to determine fastest paths and catchment areas

In the second step of the methodology, the road network with its assigned cycling speeds was used to conduct the network analysis to determine the catchment area of each stop.

The catchment area was determined as part of a 'system accessibility approach' (Malekzadeh and Chung, 2019) – meaning that the focus was put on the access/egress journey and not on the public transport service, its frequency, reach and reliability. While this constitutes a simplification of a complex system, it allows for a better understanding of the accessibility conditions of the public transport service as a whole, assuming that the number of potential users and destinations are distributed proportionally around the public transport stops (Midenet et al., 2018). In a first step, a circular buffer with a radius of 2.5 km was applied around each public transport stop to delimit the case study area and select only the building centroids within the area. The value of 2.5 km was selected based on findings in the literature suggesting that that distance is acceptable for first- or last-mile trips to/from public transport stops (Hochmair, 2015; Lee et al., 2016; Martens, 2004; Midenet et al., 2018).

The resulting road network with assigned cycling speeds is then used in the network analysis performed with the QNEAT3 algorithm 'OD Matrix from Layer as Lines (m:n)' to determine the fastest paths (time optimisation) between all the building centroids and the public transport stops that are within 2.5 km Euclidean distance. The road network and the assigned cycling speeds, as well as the two point layers – the 'origin' layer containing all the building centroids (origin points – OPs), and the 'destination' layer containing all the light rail stops (destination points – DPs) – are the input layers and variables, and the output is a layer that contains the fastest paths that connect all building centroids to the public transport stops that are within 2.5 km Euclidean distance. Of all the fastest paths for each centroid, then, the overall fastest is selected and the centroid is assigned to the catchment area of the stop it is connected to. Fig. 1a and Fig. 1b show a simplified example of this process, using a random point A to illustrate how the network analysis was carried out. In Fig. 1a, point A is shown along with the road network characterised by the different assigned cycling speeds and the light rail stops in the area. In Fig. 1b, the calculation of the network analysis tool is illustrated: using the assigned cycling speeds and the road network geometry, the fastest path from point A to all the public transport stops within 2.5 km Euclidean distance is calculated. Of all the fastest paths – in the case of point A, four fastest paths were determined – the overall fastest is selected (travel time optimisation). In the example, the route from point A to 'Blackhorse' stop is the connection that is fastest overall. Therefore, in the model, point A is assigned to the catchment area of 'Blackhorse' stop. It is important to remember, however, that as outlined above, while the algorithm determines the fastest route, in reality this is the optimal route based on infrastructure availability, quality and safety,

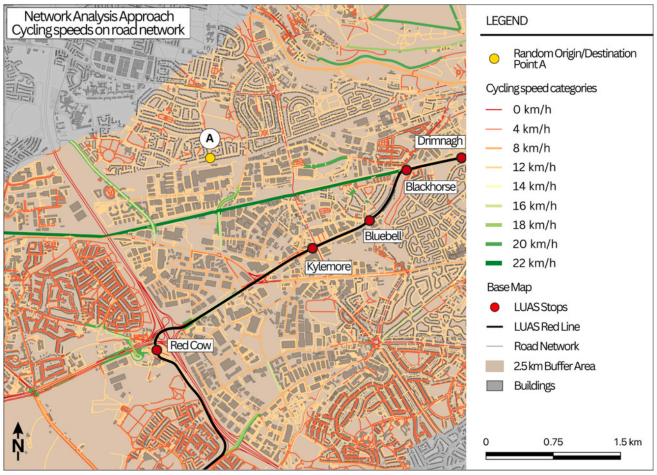


**Fig. 1a.** Cycling speeds assigned to the road segments in the case study area.

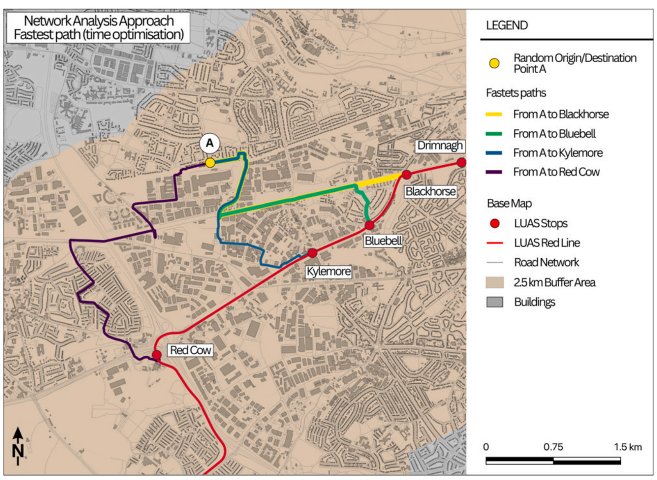


**Fig. 1b.** Fastest routes from point A to the four stops that are within 2.5 km Euclidean distance.

not necessarily the fastest route, given that the cycling speeds assigned to each segment in the model do not correspond to actual or empirical cycling speeds measured on those segments. This example shows that, when using this approach based on infrastructure quality, points are assigned to the catchment areas of stops that are further away (both greater Euclidean distance and route length) but are ultimately connected by routes with better infrastructure.

### 3.2. *Micromobility and public transport integration (MPTI) index*

Once the network analysis has been carried out and the catchment area determined for each stop, a series of indicators are calculated to quantify the level of connectivity and suitability of the catchment areas and the stop itself for micromobility use. The indicators, which are used to determine the micromobility and public transport integration index, are listed in Table 1 and explained in more detail in the following. The selection of the criteria and indicators is based on findings from the literature and the relevant sources are cited for each point, where relevant.

#### 3.2.1. *Network analysis indicators*

The Network analysis indicators shown in Table 1 are determined following the catchment area analysis and the fastest routes connecting each stop to all the origin points (OPs) within its catchment area.

**Table 1**
Index components, criteria and weights.

| Index components | Weight | Scores | Weight | Indicators | Weight |
|---|---|---|---|---|---|
| $I_N$ Network analysis index | 0.5 | $S_{OPs}$ Spatial reach (number of destinations) | 0.2 | Number of OPs in catchment area divided by number of OPs in Nearest hub polygon | 1 |
| | | $S_{Length}$ Spatial reach (average length of routes) | 0.2 | Average length of routes | 1 |
| | | $S_{Directness}$ Route directness | 0.2 | Length of routes divided by Euclidean distances | 1 |
| | | $S_{Speed}$ Average speed | 0.2 | Percentage of routes with an average speed > 12 km/h | 1 |
| | | $S_{Slope}$ Topography | 0.2 | Slope of routes determined every 500 m | 1 |
| $I_S$ Stop analysis index | 0.5 | $S_{Accessibility}$ Accessibility of stop | 0.25 | Accessibility score | 0.8 |
| | | | | Stop is located on street level | 0.2 |
| | | $S_{Infrastructure}$ Cycling infrastructure | 0.25 | Availability of cycling infrastructure in the immediate surroundings of the stop | 0.5 |
| | | | | Type of infrastructure available within 250 m of the stop | 0.5 |
| | | $S_{Parking}$ Parking availability at stop | 0.25 | Type of free & publicly accessible parking, and capacity | 0.8 |
| | | | | Availability of bicycle lockers for rent, and capacity | 0.2 |
| | | $S_{Sharing\_Station}$ Bicycle sharing station | 0.25 | Availability of a bicycle sharing station within 200 m (walking distance along network) of the stop | 1 |

3.2.1.1. *Spatial reach (OPs reached/OPs nearest).* For each public transport stop the number of buildings (referred to in the following as origin points / OPs) connected to the stop via the fastest path is calculated and divided by the number of OPs that are within the Thiessen polygon for the stop. This ratio is an indicator of how well connected the stop is to its surrounding area. The first spatial reach score, $S_{OPs}$, is calculated for each stop $i$ as shown in Eq. (1):

$$S_{OPs_i} = \frac{N_{OPs_{Network_i}}}{N_{OPs_{Hub\,i}}} \tag{1}$$

with $N_{OPsNetwork}$ being the number of OPs connected to each stop $i$ via the fastest path and $N_{OPsHub}$ being the number of OPs that lie within the 'Hub polygon' of each stop $i$. The scores obtained for each of the stops are normalised using min–max normalisation (to obtain values between

0 and 1) as shown in Eq. (2):

$$S_{i_{norm}} = \frac{S_i - S_{min}}{S_{max} - S_{min}} \tag{2}$$

*3.2.1.2. Spatial reach (average length of routes).* For each OP, the length of the route along the network is calculated. The average length of routes for each stop gives an indication of the spatial reach of the stop. The second spatial reach score, $S_{Length}$, is therefore calculated for each stop $i$ as shown in Eq. (3):

$$S_{Length_i} = \frac{\sum_{m_i} L_{m_i}}{m_i} \tag{3}$$

with $L_m$ being the length of each route $m$ connected to each stop $i$ in the public transport network. The scores obtained for all the stops were then normalised using min–max normalisation, as shown in Eq. (2).

*3.2.1.3. Route directness.* Route directness is identified as a significant factor in determining route choice for both cycling (Caulfield et al., 2012) and e-scooter use (Zhang et al., 2021). Kircher et al. (2018) stress the importance of efficient and safe infrastructure to promote cycling and attract a variety of user groups. Similarly, Dill (2009) found that minimising trips distances was of equal importance to cyclists as the availability of safe cycling infrastructure, while Hardinghaus et al. (2021) reported the hindering effect of low directness on propensity to cycle. Assessing the availability of safe infrastructure alone is therefore not sufficient, the directness of the routes has to be taken into account when calculating the quality of the network for micromobility use in the catchment area. A graphic explanation of the directness factor is presented in Fig. 2, where two points, A and B, are shown as well as the route along the network and the Euclidean distance. Fig. 2 underlines the importance of permeability, showing that, while point A can be reached along a route that is only slightly longer than the Euclidean distance, the route to reach point B is a lot longer than the Euclidean distance. The route directness factor is a useful tool to determine barrier effects and low permeability in certain areas, which could point to the need for infrastructure improvements to increase accessibility. The directness score $S_{Directness}$ is defined as the average of the directness of all routes for each stop $i$ and is calculated as shown in Eq. (4):

$$S_{Directness_i} = \frac{\sum_{m_i} \frac{L_{m_i}}{d_{m_i}}}{m_i} \tag{4}$$

with $L_m$ being the distance along each route $m$, and $d_m$ being the Euclidean distance associated with each route $m$ for each stop $i$. The closer the value is to 1, the more direct the route is. The scores obtained

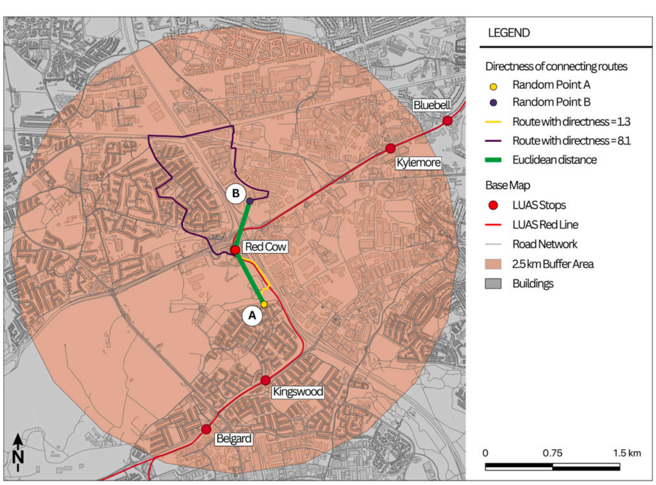


**Fig. 2.** Illustration of the route directness factor of two random points A and B.

for all stops are then normalised using min–max normalisation (see Eq. (2)) with 1 being set as the minimum value.

*3.2.1.4. Percentage of routes with an average assigned cycling speed greater than 12 km/h.* The average assigned cycling speed on the network for each route is determined by dividing the distance along the network by the travel time (the travel time 'cost' is calculated in the Origin-Destination (OD) matrix for each OD pair). For each stop, then, the percentage of routes with an average assigned cycling speed >12 km/h is determined. 12 km/h is the threshold for adequate cycling infrastructure (anything below is not considered 'cyclable' both in terms of safety and comfort, as outlined in Appendix A, Table A.1). Therefore, by determining the percentage of routes with an adequate infrastructure throughout, we can assess the quality of the cycling infrastructure in the catchment area of each stop. The average assigned cycling speed score, $S_{Speed}$ is calculated for each stop $i$ as shown in Eq. (5):

$$S_{Speed_i} = \frac{N_{AvSpeed>12_i}}{N_{tot i}} \tag{5}$$

with $N_{AvSpeed}$ being the number of routes with an average assigned cycling speed of over 12 km/h for each stop $i$, and $N_{tot}$ being the total number of routes for each stop $i$. The scores obtained for the stops are values between 0 and 1 and are not normalised further.

*3.2.1.5. Topography.* The topography of an area and more specifically the slope of routes or route sections has been identified as another significant determinant of route choice for cycling, with slopes of 4 % or higher being perceived as barriers to cycling (e.g. Codina et al., 2022; Grigore et al., 2019; Krenn et al., 2015). While slope could have been integrated into the earlier network analysis to influence fastest-path routing, it was treated as a separate factor to reflect its varying relevance across micromobility modes. For electrically assisted vehicles like e-bikes and e-scooters, slope has minimal impact on travel time, so isolating it allows flexibility to adjust its influence based on local mode characteristics. In this study, slope was included as a stop-level component with equal weight. We acknowledge that incorporating slope into speed assignments would better reflect time-based optimisation for non-assisted bicycles. Future iterations could integrate slope-adjusted speeds to enhance alignment with user effort and infrastructure interaction.

On each route connecting an origin/destination point to a stop, the elevation was determined every 500 m along the route using the Digital Elevation Model (DEM) for Ireland. The slope was then calculated for each segment. For segments and routes shorter than 500 m the slope was not calculated, under the assumption that, in a case study area such as Dublin, that is relatively flat, for such short distances the slope can be neglected. However, it should be noted that in case study areas with a hillier terrain, a shorter segment distance should be used to account for short, steep slopes. The slopes are categorised as shown in Table 2 and then interpolated for the whole route by summing up all values and dividing by the number of segments per route. The Slope score $S_{Slope}$ is therefore calculated for each stop $i$ as shown in Eq. (6):

**Table 2**
Slope categories and their distribution on the segments of the road network.

| Slope | Category SC | N. of Segments | % of total segments |
|---|---|---|---|
| Not determined* | 0 | 15,218 | 1.95 % |
| 0–2 % | 1 | 685,510 | 88.01 % |
| 2–4 % | 2 | 73,187 | 9.40 % |
| 4–6 % | 3 | 4,105 | 0.53 % |
| 6–8 % | 4 | 603 | 0.08 % |
| >8 % | 5 | 302 | 0.04 % |
| Total | – | 778,925 | 100 % |

* Not determined refers to routes shorter than 500 m where the slope has not been calculated.

$$S_{Slope_i} = \frac{\sum_{m_i} \frac{\sum_{n_{m_i}} SC_{n_{m_i}}}{n_{m_i}}}{m_i} \tag{6}$$

with $SC_n$ being the slope category (see Table 2) for each route segment $n$ and $m$ being the total number of routes for each stop $i$. The scores are then normalised using a min–max normalisation with the minimum value being 0 and the maximum value being 5 (as per Table 2).

The network analysis index $I_N$ is then calculated for each stop $i$ combining the five scores introduced above and their respective weights listed in Table 2, as shown in Eq. (7):

$$I_{N_i} = \left[0.2^*S_{OPs_i} + 0.2^*S_{Length_i} + 0.2^*\left(1 - S_{Directness_i}\right) + 0.2^*S_{Speed_i} + 0.2^*\left(1 - S_{Slope_i}\right)\right]^*N_{OPs_i} \tag{7}$$

with $N_{OPs}$ being the normalised number of origin points that can be reached from each stop. Adding this factor allows to scale the network analysis index $I_N$ according to the spatial reach and relative importance of each stop. It should be noted here that the scores for directness and slope, $S_{Directness}$ and $S_{Slope}$, have a negative effect on the overall score in that a higher value has a negative impact on micromobility use, and therefore the complementary value $(1 - S_i)$ was used in the calculation.

### 3.2.2. Stop indicators

Subsequently, the stop scores are determined as outlined in Table 3. Each of the scores is introduced and explained in the following.

*3.2.2.1. Accessibility of stop.* The accessibility of each stop refers to the permeability of the surrounding area and the points of access to the stop (defined as accessibility score, see below) as well as whether the stop is situated at street level or not. Lahoorpoor and Levinson (2020) analysed access to train stations and found that the number of access points (or gates) significantly influences accessibility and access time. Public transport stops with good accessibility are not only easier and faster to reach, the ease of access also positively influences comfort and user experience (Zhang and Lee, 2023).

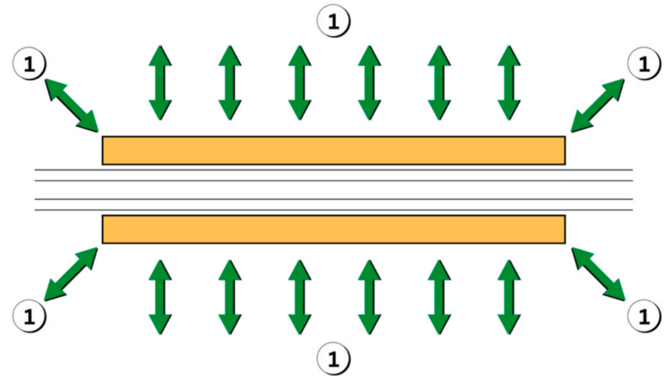


**Fig. 3.** Schematic representation of the objective assessment of station/stop accessibility.

The accessibility score is determined by evaluating the number of access directions at each stop as illustrated in Fig. 3 and can have a value between 1 (lowest score) and 6 (highest score). The reduction of accessibility posed by the presence of stairs or elevators when the stop is not on street level (Andersen and Landex, 2008) has also been added to the accessibility score using a binary variable (1 for the stops that are on

**Table 3**
Stop indicators, measures and levels.

| | Scores | Indicators | Measures | Categories | Levels |
|---|---|---|---|---|---|
| Stop characteristics | Accessibility of stop | Accessibility score | Number of access points to the stop | 1 | 0.167 |
| | | | | 2 | 0.333 |
| | | | | 3 | 0.5 |
| | | | | 4 | 0.667 |
| | | | | 5 | 0.833 |
| | | | | 6 | 1 |
| | | Stop is located on street level | Absence of stairs, lifts, ramps | No | 0 |
| | | | | Yes | 1 |
| | Cycling infrastructure | Availability of cycling infrastructure in the immediate surroundings of the stop | Infrastructure available | No | 0 |
| | | | | Yes | 1 |
| | | Type of infrastructure available within 250 m of the stop | Ratio of type of infrastructure and whole network | 1 | 0.333 |
| | | | | 2 | 0.667 |
| | | | | 3 | 1 |
| | Bicycle parking availability at stop | Type of free & publicly accessible bicycle parking, and capacity | Type of bicycle parking multiplied by capacity | No bicycle parking available | 0 |
| | | | | Sheffield stands, not sheltered | 0.333 |
| | | | | Sheffield stands, sheltered | 0.667 |
| | | | | Sheltered and secured parking | 1 |
| | | Availability of bicycle lockers for rent | Availability multiplied with capacity | No | 0 |
| | | | | Yes | 1 |
| | Bicycle sharing station | Availability of a bicycle sharing station within 200 m (walking distance along network) of the stop | Bicycle sharing station available in urban or suburban context | No | 0 |
| | | | | Yes, urban | 0.5 |
| | | | | Yes, suburban | 1 |

street level, 0 for those that are either under or over the street level).

Eq. (8) shows how the accessibility score is determined for each stop:

$$S_{Accessibility_i} = 0.8 * F_{Ai} + 0.2 * \beta_{SL_i} \tag{8}$$

with $F_A$ being the normalised accessibility factor determined for each stop $i$ as outlined above, and $\beta_{SL}$ being the binary variable indicating whether each stop $i$ is located at street level or not. Good accessibility and permeability of the surrounding area are desirable qualities for public transport stops and stations. However, many factors can influence the accessibility level and other requirements (such as safety) might have priority or constraints given by the built environment might limit accessibility. Nevertheless, it is an important factor to consider carefully when planning public transport stops or when analysing the catchment area and reach, since it can have a significant impact on access travel times, user experiences, and comfort (Andersen and Landex, 2008).

*3.2.2.2. Infrastructure available at stop.* The quality of the infrastructure in close proximity of the stop has been found to be a significant predictor for micromobility use in access and egress trips. Kosmidis and Müller-Eie (2023) reviewed a number of studies and found that the lack of cycling infrastructure in the immediate vicinity of a stop was perceived as a barrier. This variable indicates whether cycling infrastructure is available in the immediate surroundings of each stop and what type of infrastructure is available within 250 m of the stop. To calculate this, the road network around each stop is selected within a circular buffer of 250 m around the stop. For each stop then, the total length of infrastructure is summed up per type and divided by the total length of the network within the buffer. To account for the different quality levels a weighting system is used (see Table 4).

To determine the infrastructure score for each stop, the segment lengths in each category are summed up as shown in Eq. (9):

$$S_{Infrastructure_i} = \beta_{I_i} * \frac{\sum_j L_{ij} * w_j}{L_{tot\,i}} \tag{9}$$

with $\beta_I$ being the binary variable indicating whether any cycling infrastructure is available at each stop $i$, $L_{ij}$ being the sum of all the segments in the area immediately surrounding each stop $i$ in category $j$, $w_j$ being the weight for each category $j$, and $L_{tot}$ being the total length of the road network within the area immediately surrounding each stop $i$. The scores obtained for each stop are values between 0 and 1 and are not normalised further.

*3.2.2.3. Parking availability at stop.* Oeschger et al. (2020, 2023) found that the availability of secure and sheltered parking is one of the determining factors in mode choice for access and egress trips with private vehicles, and in particular the availability of sheltered and secured parking facilities to use free of charge. Kosmidis and Müller-Eie (2023) identified several significant factors that influence cycling for access and egress trips in their literature review, such as capacity; distance of the parking facility to the stop, with users preferring those facilities closest to the stop, even if less secure; level of security provided, with users preferring secured and monitored parking facilities; payment, which was found to have a negative impact on bicycle use. These findings suggest that the availability of bicycle parking in close proximity of the stop is of utmost importance. Additionally, the quality of the facilities significantly influences the probability of micromobility use for access and egress trips, with sheltered and secured parking facilities being the most desirable ones. Given the negative impact of paid bicycle parking facilities, these were included separately in the methodology, to account for the fact that, while they provide a level of security, they are not the preferred option to attract a large number of users.

**Table 4**
Different categories of assigned cycling speeds and corresponding weights.

| Category $j$ | Assigned Cycling Speed | Weight $w_j$ |
|---|---|---|
| 0 | 0 km/h | 0 |
| 1 | 4 km/h to 8 km/h | 0.333 |
| 2 | 12 km/h to 16 km/h | 0.667 |
| 3 | 18 km/h to 22 km/h | 1 |

The parking score $S_{Parking}$ is calculate as shown in Eq. (10):

$$S_{Parking_i} = 0.8 * \left( \sum_k C_{ik} * w_k \right) + 0.2 * \beta_{il} * C_{il} \tag{10}$$

with $C_{ik}$ being the normalised parking capacity for each category $k$ of free and publicly available parking facilities at each stop $i$, $w_k$ being the weight associated with each category $k$ (see Table 4), $\beta_{il}$ being the binary variable indicating whether secured parking at a cost is available at each stop $i$, and $C_{il}$ being the normalised capacity of the paid parking facilities. The two capacity factors, $C_{ik}$ and $C_{il}$, are normalised using min–max normalisation (see Eq. (2)).

*3.2.2.4. Sharing station availability within 200 m of stop.* Station-based bicycle sharing services are typically placed in close proximity of public transport stops and stations to facilitate and encourage intermodal trips (Campbell and Brakewood, 2017). The findings from the literature are not conclusive, with some studies suggesting that sharing services are used to complement public transport service, while others suggest that sharing services are competing with public transport services – particularly in dense urban areas such as the city centre. Nevertheless, a number of researchers underline the beneficial long-term effects that can result from the introduction and promotion of sharing-services in combination with public transport (e.g. Campbell and Brakewood, 2017; Kong et al., 2020; Martin and Shaheen, 2014; McQueen and Clifton, 2022; Mohiuddin et al., 2023; Singleton and Clifton, 2014).

The availability of bicycle-sharing stations within 200 m walking distance of a stop was included in the index as sharing station score $S_{Sharing\_Station}$. Sharing stations located in dense urban areas are more likely to have a competing rather than complementing effect, compared to sharing stations located in less dense, suburban areas, where shared modes are more likely to be used for access and egress trips (Martin and Shaheen, 2014; van Kuijk et al., 2022; Nawaro, 2021; Yan et al., 2021). Therefore, the score has a value of 0 if no sharing station is available, a value of 0.5 if the public transport stop is located in the city centre (dense urban areas) and a value of 1 for stops outside the city centre (suburban areas) – as listen in Table 4.

Further research and new findings should be considered and the factors adjusted accordingly, if necessary.

The station analysis index is then calculated by adding up the weighted and normalised scores as shown in Eq. (11):

$$I_S = 0.25 * S_{Accessibility} + 0.25 * S_{Infrastructure} + 0.25 * S_{Parking} + 0.25 * S_{Sharing_{Station}} \tag{11}$$

*3.2.3. Compiling the micromobility and public transport integration (MPTI) index*

Once the two components of the index have been determined, the two values are summed with equal weights as shown in Eq. (12):

$$I_{MDPI} = 0.5 * I_N + 0.5 * I_S \tag{12}$$

The resulting index is a value between 0 and 1, with 0 representing a stop that is wholly inadequate and unattractive for access or egress trips using micromobility and 1 a stop that is characterised by optimal infrastructure to promote multimodal trips, both at the stop itself as well as in the catchment area surrounding it.

*3.2.4. Index calculation*

Each of the four stop-level indicators was assigned an equal weight of 0.25 in the final index. This uniform weighting approach reflects a normative assumption that all indicators contribute equally to

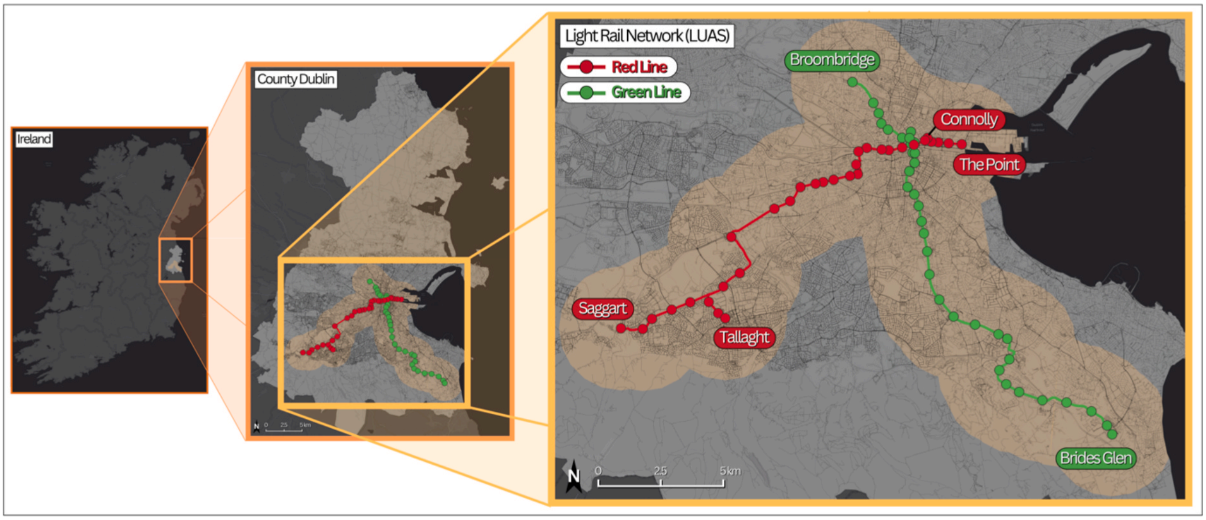


**Fig. 4.** Case study area: Light Rail Network (Luas) in Dublin, Ireland.

integration quality. However, future iterations and improvements to the index could incorporate stakeholder input to derive policy-specific weightings.

### 3.3. *The case study area: Dublin's light rail network (Luas)*

The methodology was tested by calculating the index for the Light Rail Network of Dublin (called Luas) consisting of two lines, the Red and the Green line (see Fig. 4). The holistic assessment proposed in this study gives a number of valuable insights that can be used to improve and streamline the efforts to make the Luas more accessible and encourage access and egress trips using micromobility.

## 4. Results

The results are presented in 3 sections. First, results obtained from the network and catchment area analysis are presented. In a second section, the results obtained for the stop analysis are outlined. Lastly, the index values calculated for the light rail network stops are presented.

**Table 5**
Statistics of the network analysis, for all stops and for the two lines separately.

| Statistics | | OPs reached/OPs nearest | Average length of routes | Directness | Adequate infrastructure | Slope | Spatial reach | Network-Index |
|---|---|---|---|---|---|---|---|---|
| | | $S_{OPs}$ | $S_{Length}$ | $S_{Directness}$ | $S_{Speed}$ | $S_{Slope}$ | $N_{OPs}$ | $I_n$ |
| Min | All stops | 0 | 0 | 0.131 | 0 | 0 | 0 | 0 |
| | Red Line | 0 | 0 | 0.131 | 0 | 0 | 0.001 | 0 |
| | Green Line | 0.001 | 0.019 | 0.144 | 0 | 0 | 0 | 0 |
| Max | All stops | 1 | 1 | 1 | 0.712 | 0.345 | 1 | 0.380 |
| | Red Line | 1 | 0.607 | 0.762 | 0.513 | 0.232 | 0.847 | 0.380 |
| | Green Line | 0.100 | 1 | 1 | 0.712 | 0.345 | 1 | 0.354 |
| Mean | All stops | 0.040 | 0.237 | 0.346 | 0.125 | 0.161 | 0.186 | 0.075 |
| | Red Line | 0.051 | 0.229 | 0.342 | 0.086 | 0.154 | 0.167 | 0.067 |
| | Green Line | 0.030 | 0.245 | 0.350 | 0.159 | 0.167 | 0.202 | 0.082 |
| Standard Dev. | All stops | 0.121 | 0.176 | 0.146 | 0.182 | 0.077 | 0.220 | 0.090 |
| | Red Line | 0.174 | 0.156 | 0.119 | 0.148 | 0.068 | 0.222 | 0.094 |
| | Green Line | 0.025 | 0.195 | 0.169 | 0.205 | 0.085 | 0.220 | 0.088 |
| Median | All stops | 0.021 | 0.203 | 0.337 | 0.011 | 0.188 | 0.074 | 0.026 |
| | Red Line | 0.019 | 0.208 | 0.343 | 0.002 | 0.188 | 0.071 | 0.025 |
| | Green Line | 0.022 | 0.203 | 0.313 | 0.051 | 0.187 | 0.105 | 0.044 |
| Q1 | All stops | 0.006 | 0.100 | 0.250 | 0.000 | 0.118 | 0.026 | 0.009 |
| | Red Line | 0.004 | 0.095 | 0.263 | 0.000 | 0.120 | 0.022 | 0.008 |
| | Green Line | 0.018 | 0.101 | 0.240 | 0.000 | 0.118 | 0.038 | 0.014 |
| Q3 | All stops | 0.034 | 0.345 | 0.396 | 0.224 | 0.208 | 0.276 | 0.115 |
| | Red Line | 0.029 | 0.359 | 0.399 | 0.097 | 0.196 | 0.239 | 0.109 |
| | Green Line | 0.035 | 0.318 | 0.382 | 0.268 | 0.222 | 0.337 | 0.124 |
| IQR | All stops | 0.027 | 0.245 | 0.146 | 0.224 | 0.090 | 0.250 | 0.106 |
| | Red Line | 0.024 | 0.264 | 0.137 | 0.097 | 0.077 | 0.216 | 0.100 |
| | Green Line | 0.017 | 0.217 | 0.142 | 0.268 | 0.104 | 0.299 | 0.110 |

**Table 6**
Statistics of the station analysis for all stops and for the two lines separately.

| Statistics | | Accessibility | Cycling Infrastructure | Bicycle Parking | Bicycle-sharing Station | Stop-Index |
|---|---|---|---|---|---|---|
| | | $S_{Accessibility}$ | $S_{Infrastructure}$ | $S_{Parking}$ | $S_{Sharing\_Station}$ | $I_s$ |
| Min | All stops | 0.160 | 0 | 0 | 0 | 0.040 |
| | Red Line | 0.160 | 0 | 0 | 0 | 0.100 |
| | Green Line | 0.160 | 0 | 0 | 0 | 0.040 |
| Max | All stops | 1 | 0.597 | 0.800 | 0.5 | 0.496 |
| | Red Line | 1 | 0.597 | 0.800 | 0.5 | 0.496 |
| | Green Line | 1 | 0.568 | 0.636 | 0.5 | 0.488 |
| Mean | All stops | 0.573 | 0.313 | 0.117 | – | 0.288 |
| | Red Line | 0.669 | 0.313 | 0.101 | – | 0.306 |
| | Green Line | 0.485 | 0.312 | 0.132 | – | 0.271 |
| Standard Dev. | All stops | 0.235 | 0.232 | 0.149 | – | 0.110 |
| | Red Line | 0.236 | 0.234 | 0.138 | – | 0.100 |
| | Green Line | 0.198 | 0.234 | 0.159 | – | 0.117 |
| Median | All stops | 0.520 | 0.441 | 0.082 | – | 0.278 |
| | Red Line | 0.680 | 0.425 | 0.082 | – | 0.289 |
| | Green Line | 0.520 | 0.442 | 0.082 | – | 0.258 |
| Q1 | All stops | 0.360 | 0.000 | 0.041 | – | 0.209 |
| | Red Line | 0.520 | 0.000 | 0.041 | – | 0.232 |
| | Green Line | 0.360 | 0.000 | 0.031 | – | 0.182 |
| Q3 | All stops | 0.680 | 0.495 | 0.133 | – | 0.366 |
| | Red Line | 0.840 | 0.493 | 0.126 | – | 0.379 |
| | Green Line | 0.680 | 0.502 | 0.159 | – | 0.359 |
| IQR | All stops | 0.320 | 0.495 | 0.092 | – | 0.156 |
| | Red Line | 0.320 | 0.493 | 0.085 | – | 0.147 |
| | Green Line | 0.320 | 0.502 | 0.128 | – | 0.177 |

### 4.1. Network analysis

In Table 5 the statistical measures for the network analysis are presented. The five categories used to calculate the network index in the catchment area of each station reveal areas or aspects in need of further or closer inspection. For example, low values in the 'Adequate Infrastructure' column indicate that the infrastructure in the catchment area is not adequate to promote micromobility use for access and egress trips. At the same time, high values in the 'Directness' column indicate that there are barrier effects or that the area is characterised by low permeability or inadequate infrastructure along the more direct routes, which should also be investigated further. The network analysis index combines the catchment area characteristics that have been determined and is a useful tool to assess and compare the spatial reach and quality of

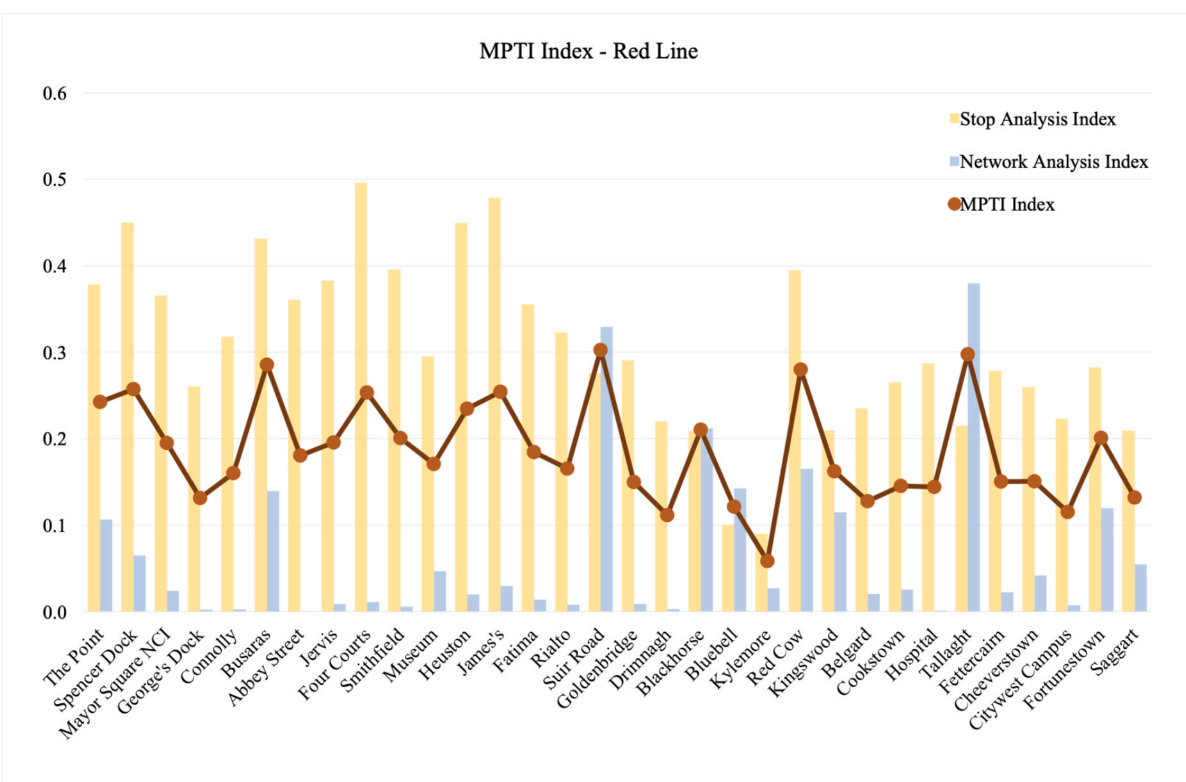


**Fig. 5.** MPTI Index and its two components for each stop on the Red Line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

infrastructure of the light rail stops within the case study area. As shown in Table 5, the maximum value obtained is 0.380, with 1 being the maximum value that could have been obtained, representing a stop that is ideally connected to its surrounding catchment area for micromobility use. The average value obtained for all stops is 0.075, which indicates that the quality of infrastructure and the attractiveness of the stops analysed could be significantly improved. This low average score reflects real infrastructure constraints in the Dublin light rail network. These values are min–max normalised within the case study area to highlight relative disparities across stops. While this approach is useful for internal comparability for transport authorities and other stakeholders, broader benchmarking with other cities would require further calibration. While the weighting scheme adopted in this study is grounded in published literature, we recognise the value of involving stakeholders in refining indicator priorities and thresholds, which was beyond the scope of this paper.

### 4.2. Stop analysis

Table 6 presents the descriptive statistics of the analysis. The stop analysis index quantifies the different aspects considered for each stop: accessibility, cycling infrastructure, bicycle parking, and availability of bicycle sharing stations.

In the first column, the accessibility score is reported. The infrastructure score, reported in the second column of Table 6 shows that a number of stops on both lines do not have any cycling infrastructure available directly at the stop. In the third column, the quality and capacity of the parking facilities available at the stops are condensed into the parking score. The fourth column presents the bicycle-sharing score. Due to the fact that all bicycle-sharing stations are located within the Dublin City Centre area the score given to these stops is 0.5, since research has shown that sharing stations located in dense urban areas are more likely to have a competing rather than complementing effect, compared to sharing stations located in less dense, suburban areas, where shared modes are more likely to be used for access and egress trips (Martin and Shaheen, 2014; van Kuijk et al., 2022; Nawaro, 2021; Yan et al., 2021).

The stop index is then calculated as a sum with equal weights of these four scores. As can be seen in Table 6, the maximum value obtained in the analysis is 0.496 while the maximum value for the Green Line stops is 0.488. The average value for all stops is 0.288. The maximum possible value is 1, indicating a stop that is ideally suited for the integrated use of micromobility and public transport. Therefore, the index indicates that all stops could benefit from further improvements, particularly in terms

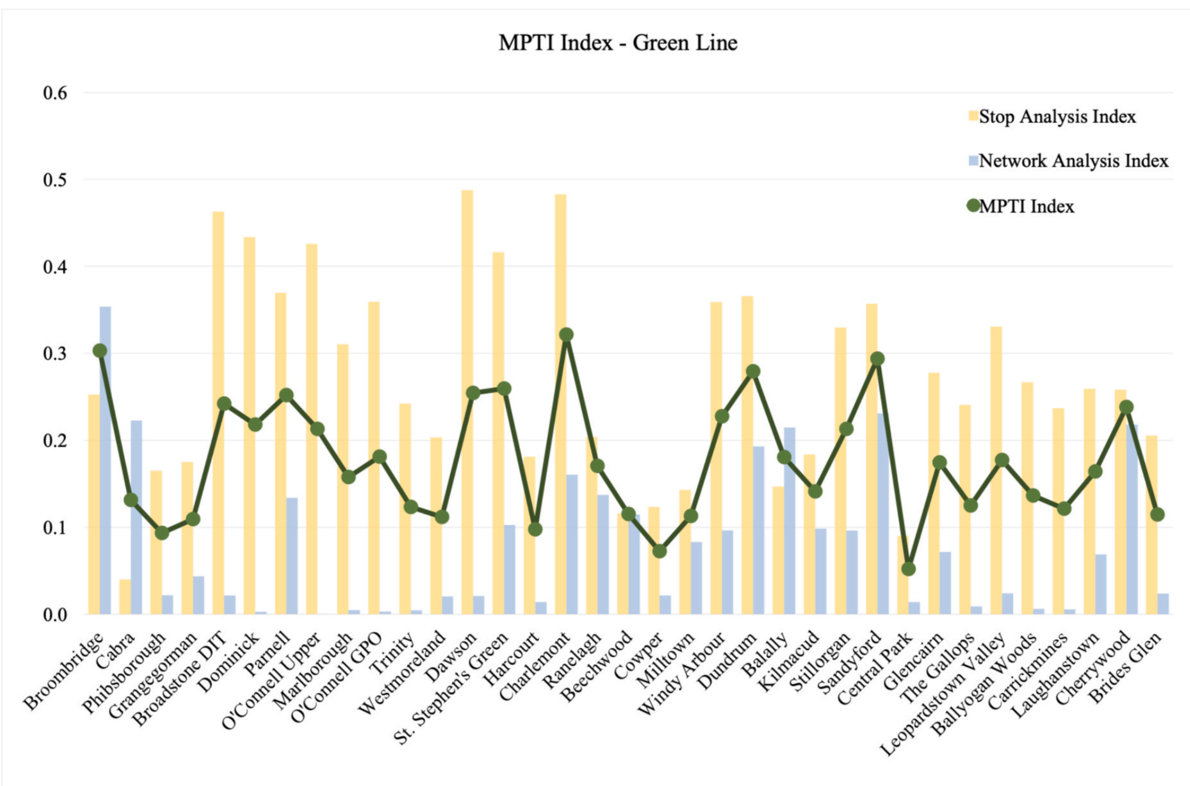


**Fig. 6.** MPTI Index and its two components for each stop on the Green Line. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

of cycling infrastructure available in the area immediately surrounding the stops, and safe and secure parking availability.

### 4.3. Micromobility and public transport integration index

Once the two indices have been calculated, they are combined to determine the overall micromobility and public transport integration index by using Eq. (11). This combined value summarises all the indicators that are relevant to quantify and assess the quality and attractiveness of a stop and its catchment area for micromobility use in access and egress trips. Fig. 5 shows the distribution of overall MPTI scores by stop, with colour gradients indicating relative performance. Scores below 0.1 represent limited micromobility support, while scores above 0.3 indicate more integrated infrastructure and built environments. Fig. 5 illustrates stop analysis and network analysis indices, alongside the MPTI index for each stop along the Red Line. Fig. 6 shows the same for the Green Line. The authors want to emphasise that, while the scale of the y-axis in Fig. 5 and Fig. 6 has a maximum value of 0.6 (for graphical reasons), the maximum index value that could be obtained is 1 and the results should be read keeping that in mind. Fig. 5 and Fig. 6 allow to easily compare the stops and their different scores as well as the overall index and visualise how the MPTI Index could be useful to planners and service providers to identify the stops to prioritise in terms of infrastructure improvements and efforts to promote the integrated use of micromobility and light rail. For example, Fig. 6 shows that improvements at the 'Tallaght' stop could increase the MPTI index of the stop which has a relatively high network analysis index, an indication of relatively good infrastructure and connectivity within the catchment area of the stop.

Similarly, in Fig. 6, the network analysis value for the 'Charlemont' stop is relatively low while the stop index is relatively high, therefore an improvement of the infrastructure in the catchment area and the provision of more direct routes could improve the overall quality and user

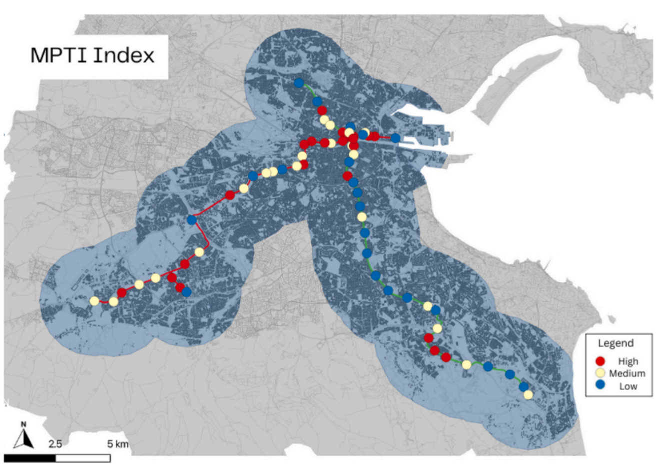


**Fig. 7.** Dublin's light rail network displaying MPTI index results and catchments areas.

experience for the integrated use of micromobility and public transport. The overall index allows to compare the values of the different and adjacent stops to identify those with a higher spatial reach and infrastructure conducive to the integrated use of micromobility and light rail. For the red line, the maximum value is obtained for the 'Suir Road' stop (0.302), while for the green line, the highest value has been determined for the 'Charlemont' stop (0.322). Additionally, Fig. 5 and Fig. 6 show that stops with higher index values (particularly when looking at the network analysis index) are followed or preceeded by stops with lower values, showing that those stops with better infrastructure make the stops in their proximity less attractive. This is due to the fact that the catchment areas are determined based on infrastructure availability and quality and therefore, stops that are surrounded by good infrastructure are better connected to a higher number of origin points, even those of stops that would be closer, when considering distance alone.

The availability of relatively better infrastructure at or around a certain stop results in a higher accessibility of this stop compared to the ones surrounding it. Therefore, when planning for the integrated use of micromobility and public transport, particularly when including public transport services with relatively high stop density (compared to heavy rail for example), from a planning perspective it would make more sense to prioritise a number of stops and maximise their suitability for micromobility and public transport integration (so called 'Mobility hubs'), rather than implementing a small number of infrastructural changes at all the stops. In particular, the stops with a high network analysis index should be prioritised in terms of infrastructure improvements at the stops, since these have the highest reach.

The spatial distribution of the MPTI index for stops in Dublin's light rail network is presented in Fig. 7. The map highlights stop-level variation in public transport performance, where each node is colour-coded to indicate MPTI levels: red for high, yellow for medium, and blue for low. These results are overlaid on a 2.5 km catchment area (represented by the shaded blue buffers) around each stop, illustrating the spatial extent of potential user accessibility. The figure reveals distinct spatial disparities in service quality and accessibility along the network. Higher MPTI values (red) cluster near the city centre, suggesting better multimodal connectivity, service frequency, and amenity provision in these locations. In contrast, stops located in outer suburban areas are generally associated with lower index scores, highlighting challenges in first/last mile connectivity in suburban areas. These findings are can prove useful in clarifying spatial priorities for interventions, enhancing practical utility for planners.

## 5. Discussion

The methodology developed and implemented in this study utilised existing Open Data on infrastructure quality and safety requirements to provide a straightforward and effective way to objectively assess the degree and quality of micromobility and public transport integration for a given network and case study area. The contribution of the analysis was twofold: (i) the network analysis approach to determine the catchment area of public transport stops, and (ii) the development of a micromobility and public transport index.

(i) The network analysis approach presented in this study determines the catchment area around public transport stops and stations. Assigning varying cycling speeds to road segments to differentiate between levels of infrastructure quality and safety provides an effective methodology to determine preferential routes based on the current knowledge on route choice determinants and user preferences and requirements for cycling infrastructure.
(ii) The index, paired with additional data on current and planned passenger flows, provides a useful tool for policy makers, planners and service providers intent on improving accessibility and ridership of public transport services while also providing more sustainable alternatives to private car travel in urban and suburban contexts.

The use of infrastructure quality indicators and a network analysis component ensures that the methodology is adequate to capture suitability and comfort of specific routes, but still allows for straightforward interpretation and ease of use. This is an important characteristic when designing a methodology with reproducibility and simplicity in mind, as in this case the aim is to provide a useful and impactful tool that is simple and straightforward and can be used and interpreted by policymakers, planners, and stakeholders in different geographical contexts.

The proposed methodology has some limitations which could be addressed in further research efforts. The index developed and presented in this study is a proposed methodology to assess the quality and degree of micromobility and public transport integration at any given public transport stop or station. While the methodology was designed with reproducibility in mind, it might need to be adapted to the introduction of new technologies or to specific contexts, including or excluding factors according to different services or to local conditions.

Additionally, a number of simplifications applied in the network analysis, such as the omission of relevant aspects of the public transport service (timetable, reliability, travel times) as well as the travel direction or competition of other public transport services, could be implemented in further research to obtain more accurate preferential routes since all these factors can influence mode and route choice for access and egress trips. Including land use and population density instead of the number of origin points ($N_{OPs}$) would also provide an additional level of detail to the analysis. While the MPTI index focuses explicitly on the built environment and network-based indicators of micromobility integration, it does not account for dynamic public transport service characteristics such as frequency, reliability, or levels of demand and calibration with user behaviour data and therefore was not conducted in this study as it was out of scope. Future iterations of the MPTI index could incorporate micromobility trip logs or user survey data to assess behavioural alignment with infrastructure conditions. Future work integrating public transport service metrics and micromobility user data is recommended for refining the mode and enhancing accuracy. Also, there is an opportunity to include of demographic overlays and participatory methods to account for equity-related metrics in future work. Finally, while this study examines a single case study area, the methodology is designed to be transferable. Future research could apply the MPTI index in contrasting urban settings (including in developing cities) and to bus and BRT networks as a means of testing the sensitivity of component weights to improve generalisabiltiy and robustness.

## 6. Conclusion

The study proposes a methodology to combine different relevant factors into an index to assess the degree of infrastructure suitability for integrated micromobility and public transport use at and within the catchment area of any given public transport stop. The index allows to easily compare and assess different aspects related to the road network surrounding a stop – such as spatial reach, connectivity, slope and directness of routes – with infrastructure availability and built environment characteristics at the stop – such as parking quality and availability, accessibility, and availability of sharing services. The methodology was developed based on findings from the literature relating to user preference for infrastructure when using micromobility and applied to the case study of the light rail network of Dublin. The methodology provided a number of insights on the ease of access, barrier effects and low permeability, while also providing an assessment of the infrastructure and built environment at the stops.

The results show that the overall connectivity of the stops in their catchment areas is not conducive to micromobility use for access and egress trips. Therefore, the infrastructure in the catchment areas of the light rail network stops need to be significantly improved to promote the use of micromobility for access and egress trips. The stop analysis index, while resulting in slightly higher values for the stops in the case study area, still shows that improvements are needed in terms of infrastructure availability, accessibility and parking facilities.

The MPTI index can serve as a practical tool for policymakers to identify and prioritise investment in first/last-mile connectivity to public transport. Examples include targeting locations for new bike lanes, micromobility parking infrastructure, or shared micromobility deployment. Future validation using trip data will enhance its utility for performance monitoring.

Overall, the index developed in this study is a useful tool that uses open data to assess the infrastructure availability at public transport stops and in their catchment areas which can be applied in any geographical context. In order to successfully promote the seamless integration of micromobility and public transport, the systematic and objective assessment of relevant factors that facilitate or hinder such an integration is a necessary step, and the methodology developed in this study is a useful tool to carry out such an assessment.

## CRediT authorship contribution statement

**Giulia Oeschger:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Investigation, Formal analysis, Conceptualization. **Brian Caulfield:** Writing – review & editing, Supervision. **Páraic Carroll:** Writing – review & editing, Supervision, Project administration, Investigation, Funding acquisition, Conceptualization.

## Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Paraic Carroll reports financial support was provided by University College Dublin. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Cycle speeds based on infrastructure and adjacent motorised traffic

**Table A1**
Cycle speeds used in the analysis.

| | Motorised Traffic | No Infra | Bus Lane | | Cycle Lane | | Surface Change | | Segregated | | Traffic Free | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Speed Limit [km/h] | Cycle Speed [km/h] | Width [m] | Cycle Speed [km/h] | Width [m] | Cycle Speed [km/h] | Width [m] | Cycle Speed [km/h] | Width [m] | Cycle Speed [km/h] | Width [m] | Cycle Speed [km/h] |
| Motorway | Any | | | | | | | | | | | |
| Primary | 80 | | | | | | | | 2.5 | 14 | | |
| | | | | | | | | | > 2.5 | 16 | | |
| | 60 | | | | | | | | 2.5 | 14 | | |
| | | | | | | | | | > 2.5 | 16 | | |
| | 50 | | | | | | 2.0 | 8 | 2.5 | 16 | | |
| | | | | | | | > 2.0 | 12 | > 2.5 | 18 | | |
| Secondary | 80 | | Any | 8 | 1.5 | 8 | 2.0 | 12 | 2.5 | 16 | | |
| | | | | | > 1.5 | 12 | > 2.0 | 14 | > 2.5 | 18 | | |
| | 60 | | Any | 8 | 1.5 | 8 | 2.0 | 12 | 2.5 | 16 | | |
| | | | | | > 1.5 | 12 | > 2.0 | 14 | > 2.5 | 18 | | |
| | 50 | | Any | 8 | 1.5 | 12 | 2.0 | 14 | 2.5 | 16 | | |
| | | | | | > 1.5 | 14 | > 2.0 | 16 | > 2.5 | 18 | | |
| | 30 | 8 | Any | 12 | 1.5 | 12 | 2.0 | 14 | 2.5 | 16 | | |
| | | | | | > 1.5 | 14 | > 2.0 | 16 | > 2.5 | 18 | | |
| Tertiary | 80 | | | | 1.5 | 12 | 2.0 | 14 | 2.5 | 18 | | |
| | | | | | > 1.5 | 14 | > 2.0 | 16 | > 2.5 | 20 | | |
| | 60 | | Any | 8 | 1.5 | 12 | 2.0 | 14 | 2.5 | 18 | | |
| | | | | | > 1.5 | 14 | > 2.0 | 16 | > 2.5 | 20 | | |
| | 50 | 8 | Any | 8 | 1.5 | 14 | 2.0 | 16 | 2.5 | 18 | | |
| | | | | | > 1.5 | 16 | > 2.0 | 18 | > 2.5 | 20 | | |
| | 30 | 8 | Any | 12 | 1.5 | 14 | 2.0 | 16 | 2.5 | 18 | | |
| | | | | | > 1.5 | 16 | > 2.0 | 18 | > 2.5 | 20 | | |
| Residential/ Service access | 80 | | | | 1.5 | 14 | 2.0 | 16 | 2.5 | 18 | | |
| | | | | | > 1.5 | 16 | > 2.0 | 18 | > 2.5 | 20 | | |
| | 60 | | Any | 8 | 1.5 | 14 | 2.0 | 16 | 2.5 | 18 | | |
| | | | | | > 1.5 | 16 | > 2.0 | 18 | > 2.5 | 20 | | |
| | 50 | 8 | Any | 12 | 1.5 | 16 | 2.0 | 18 | 2.5 | 18 | | |
| | | | | | > 1.5 | 18 | > 2.0 | 20 | > 2.5 | 20 | | |
| | 30 | 12 | Any | 12 | 1.5 | 16 | 2.0 | 18 | 2.5 | 18 | | |
| | | | | | > 1.5 | 18 | > 2.0 | 20 | > 2.5 | 20 | | |
| Shared Use | 30 | 14 | | | | | | | | | | |
| | - | | | | | | | | | | 3.0 | 18 |
| | - | | | | | | | | | | > 3.0 | 20 |
| Footpath | - | 4 | | | | | | | | | | |
| Cycleway/ Greenway | - | | | | | | | | | | 3.5 | 20 |
| | - | | | | | | | | | | > 3.5 | 22 |

Note: A cycling speed of 0 km/h is assigned to all the segments where cycling is banned (e.g. motorway, primary roads, etc.) – all grey fields. Footpaths and pedestrian areas where cycling is not allowed are assigned a cycling speed of 4 km/h to represent the need for cyclists to dismount and walk.

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