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Level of Propensity: a zonal metric for evaluating the multimodal option Electric Micromobility and Public Transport

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Abstract

Electric Micromobility (EMM), e.g. e-bikes, e-scooters, light-weight electric vehicles, has a key role in policymakers' strategies for making cities more liveable. Especially, its combination with Public Transport (PT) can be essential in the transportation sector decarbonization.

This work proposes a zonal metric to evaluate EMM and PT integration, named "Level of Propensity" (LoP) to multimodality.

LoP is defined adopting a multi-dimensional domain-based classification capturing two main phases of the trip: (1) the access phase by EMM towards PT stops; (2) the accessibility potential to destination by PT. PT open data, road network configuration, activities and Floating Car Data are adopted for the elaboration.

LoP has been validated in the medium-size city of Salerno (Italy), but it is easily transferable to other cities. It can support urban planners and PT/EMM operators in identifying zones with low propensity to multimodality, suggesting priorities in terms of PT service improvements and EMM infrastructure implementations.

Keywords: Electric Micromobility; Public Transport; Accessibility; GTFS; Point of Interest (POI); Floating Car Data.

1. Introduction

Recently, innovative vehicles, emerging transport modes and novel mobility services changed in a disruptive way the transportation landscape of our cities; shared bicycles, e-bikes, e-scooters, e-mopeds, light-weight electric vehicles, e-cars, ride-hailing are just few examples. Understanding their effects in terms of environmental sustainability,

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reliability, social equity and inclusion, is fundamental to implement the right strategies for transportation planning (Eltis, 2019) and road network implementation (Fazio et al., 2021; Sorkou et al., 2022).
Focusing on Electric Micro-Mobility (EMM), defined as a range of electric, small, light-weight vehicles, typically operating at low speeds (comparable to a bicycle) and personally driven by users, the post pandemic era experienced a huge spread of their adoption, both as an owned vehicle and as a sharing service (especially for e-scooters and e-bikes). EMM, innovative, affordable, flexible, easy-handle and able to guarantee acceptable speeds, can be adopted for short-distance trips when used alone, or for longer trips when combined with public transport (first mile/last mile solution). Thus, it is considered as an efficient opportunity to integrate or even substitute traditional transport systems.

In terms of EMM adoption as a single-mode for short-distance trips, McKenzie (2020) derived typical travelled distances, reporting maximum values of about 3 km for e-scooter and 6 km for e-bikes; similar values are reported in Nigro et al. (2022). Also, elements affecting the choice of EMM have been deeply investigated in the literature: Axhausen and Reck (2021) described the socio-economic characteristics of the typical e-scooter user (young, high-income, and high level of education). Non-functional factors such as environmental concern, innovativeness, and the sense of belonging associated with using that particular transport mode can be even more important for users in choosing EMM (Bretones and Marques, 2022).

Several insights can be found about the impact of the travel environment on the adoption of EMM: Zhang et al. (2021) analysed through GPS data users' preferences regarding infrastructures, finding that EMM adoption is much more likely on bike-lanes, sidewalks (if allowed by local regulations) and tertiary roads. Moreover, Cubells et al. (2023) showed that EMM route choices are impacted by urban elements related to safety, accessibility and aesthetics, pointing out the importance of considering the surrounding environment to ensure user safety. To this regard, several studies confirmed that dedicated infrastructures (Hossein Sabbaghian et al., 2023; Greibe and Buch, 2016; Park and Abdel-Aty, 2016), which can be shared by both cyclists and e-scooter users, as well as pavement conditions (López-Molina et al., 2023; Mitropoulos et al., 2023) are key elements to micro-mobility safety perception and, consequently, to EMM adoption.

A tailored suitable infrastructure which enables cyclists and EMM users to be separated from motorists is much more likely to be chosen when compared to other safety measures. Bai and Jiao (2020) found that EMM ridership is positively impacted by the closeness to the city center, the mixed land-use and the accessibility to the public transport network. Similar results can be found in Caspi et al. (2020) and Jin et al. (2023).

Moving to the combination between EMM and Public Transport (PT), it is proven that their integration reduces car trips and, as a consequence, positively contributes to urban mobility alleviating traffic congestion and air pollution (Caggiani et al., 2020, Orozco-Fontalvo et al., 2023). Moreover, by completing first/last mile distances, one should also consider that EMM can lead to greater use of PT with an even higher positive total impact in the decarbonization of the transportation sector and in the mobility management efficiency (Møller et al., 2020; Shaheen et al., 2020). This is especially true when referred to the concept of Mobility-as-a-Service (i.e. promoting bundled pricing, Yan et al., 2023, discounts and single booking application, Yang et al., 2023),

or to specific EMM spread strategies (e.g. the location of charging stations closed to PT terminals, Altintasi and Yalchinkava, 2022).
Efforts in understanding users' behaviour related to the adoption of shared EMM for the first/last mile have been conducted mainly through survey and discrete choice modelling. For example, according to van Kuijk et al. (2022), from a sample of 499 respondents PT travellers in the city of Utrecht (both in urban and suburban environment), shared e-bikes and e-scooters are generally preferred over other shared mobility options for covering the first/last mile distances. Montes et al. (2023), using stated preference data collected in the city of Rotterdam and discrete choice modelling techniques, found that shared micromobility modes are viable alternatives as egress modes for metro trips.

Mostly of the literature about multimodality deals with the integration of (e-)bike and PT (Geurs et al., 2016, Noland et al., 2016, Zhang and Zhang, 2018), while e-scooters are only recently attracting attention (Oeschger et al., 2020). Scott and Schwieterman (2018) proved high potential of shared e-scooters in substitution of cars for trips with travel distances between 0.6 and 3 km (around 30%) and as a first/last mile solution in combination with PT (+16% accessibility to job opportunities within 30 minutes with respect to the "walk and PT" option). Baek et al. (2021) demonstrated that users positively perceived the time saving using an e-scooter in the access phase to PT system with respect to the walking access.

Although scientific literature has started to explore the implications related to the combination of EMM and PT as previously described, current studies are still lacking of a methodology able to assess and quantify EMM and PT integration. The latter is a crucial information for supporting urban planners, shared micromobility and transit operators in evaluating the current supply conditions and in suggesting strategies and priority actions to increase multimodality.

Given this framework, this contribution is aimed at bridging this lack through the definition of a zonal metric for evaluating the potential integration between EMM and PT in urban contexts, hereafter called "Level of Propensity" (LoP) to multimodality.

LoP is defined adopting a multi-dimensional domain-based classification able to capture the two main phases of a multimodal trip EMM plus PT: *(1)* the access phase by EMM towards the PT stops; *(2)* the accessibility potential to destination by PT. Open data about PT (General Transit Feed Specification – GTFS), road network configuration (Open Street Map – OSM), activities in the area (Point of Interests – PoIs, census data) and Floating Car Data (FCD) are adopted for the elaboration.

LoP has been tested and validated in the medium-sized city of Salerno (Italy), with a specific focus on the integration between e-scooters and PT.

The structure of the paper is as follows. Section 2 describes the detailed methodology for the definition of LoP. Results of its application and validation to the medium-sized city of Salerno (Italy) are discussed in Section 3. Concluding remarks and potential implications are offered in Section 4.

2. Methodology

The methodology for the definition of LoP is based on: *i)* the computation of zonal indicators describing the two different main phases of the multimodal trip EMM plus

PT and the selection of the major explanatory variables; *ii)* insertion of the explanatory variables into a multi-dimensional domain and definition of LoP thresholds.

With regard to (*i*), the two phases considered are: *(1)* the access phase by EMM to PT stops, *(2)* the accessibility potential to destination by PT. Once computed the zonal indicators, explanatory variables are selected avoiding possible variables' dependency. The step *(ii)* is the most sensitive one, since it requires the definition of LoP thresholds able to effectively highlight high or low tendency for multimodality of each zone. Along the lines of the Level of Service classification in traffic theory, the here proposed methodology wants to define different LoP levels as a function of good or bad values for each of the explanatory variable considered in the multi-dimensional analysis, while simultaneously considering the related modal shift (i.e. a higher LoP means a higher EMM plus PT usage versus a lower car adoption).

2.1. Zoning and input data

The city to be investigated is divided according to a regular hexagonal grid, 500 meters side long. This mapping allows a homogenous distribution of centroids (starting/ending points of the trip positioned in the centre of each hexagon) and a full coverage of the territory to be obtained. Thanks to its flexibility, the hexagonal shape has been widely used in spatial accessibility analysis (Burdziej, 2019): it guarantees the absence of empty spaces and overlaps, as well as the coverage of irregular boundaries.

Census data and spatial data regarding the main activities in the territory have been assigned to each area of the grid. Census data (i.e. population and employees) have been adopted as a proxy of the built environment. Specifically, these are assigned to each hexagon assuming a homogenous distribution of inhabitants and employees in each census zone. Then, the shares of inhabitants and employees are assigned to the hexagon according to the percentage of overlapping area with the census zones.

Activities to be adopted for the computation of accessibility potential to destination by PT refer to the Points of Interest (PoI) extracted from the OpenStreetMap (OSM) database using the plugin QuickOSM on QGis. The selected PoIs are amenities (e.g. restaurants, cafes, hospitals, banks), shops (e.g. supermarkets, clothing stores, shoes stores, groceries), tourism points (e.g. theatres, museums), offices (both private and public), leisure points (e.g. parks, gyms), education points (i.e. schools) and industrial buildings.

Transport supply is derived by the road network configuration and the cycle paths structure in combination with the General Transit Feed Specification data (GTFS). Road configuration and cycle path network are essential information for evaluating the accessibility by EMM to PT stops. The latter are extracted from OSM, selecting the links that can be considered "suitable for EMM", "suitable for only cars" or "suitable for both" (cars and EMM). Instead, GTFS is a geo-referenced data format defining schedules and geographic information related to PT networks. These datasets are typically open and every PT operator is required to make them accessible (EU Regulation 2017/1926). This data format includes fields describing technical specification of the service, in particular: 1) identity code, name and coordinates of each stop, 2) identity code, name, transport mode, trajectory, operator of each route, 3) identity code, reference route, timetable of each trip plus additional information such as direction of the trip, wheelchair accessibility, bike onboarding availability. Finally, trip arrival and departure times are available for each stop, as well as the position of each stop in the trip sequence is known.

Since no data are available about PT modal share, Floating Car Data (FCD) was adopted to derive indirect information regarding modal choices for defining the LoP thresholds. FCD are commercial data containing geo-referenced points of probe vehicles equipped with an On-Board Unit (OBU). The OBU sends the position (and the relative date and timestep) to the GPS system, in addition to the ID of the probe vehicle, the engine state and the travelled distance with respect to the previous tracked point. Path travel distance, travel time and dwell time could be computed for each trip, making FCD mainly used for private demand estimation (Ásmundsdóttir et al., 2010) and for descriptive statistics of travel patterns (De Vincentis et al., 2022).

2.2. EMM-PT trip, phase 1: access by EMM to PT stops, relevant indicators

The indicators from literature here selected to evaluate the access phase by EMM to PT stops are: the Micromobility Compatibility Index (MCI; Nigro et al., 2022), Density of Stops (DS; Gattuso et al., 2020), and the Public Transportation Accessibility Level (PTAL; Greater London Authority, 2015).

MCI describes the infrastructural feasibility of roads travelled by EMM. It is computed considering the traffic zones (and relative infrastructures) the single vehicle *i* moves across. Specifically, for each zone *z*, an MCI^z value is computed as the total length of network suitable for EMM (L_m^z) divided by the total length of the road network (L_c^z):

$$MCI^z = \frac{L_m^z}{L_c^z} \tag{1}$$

Then, for each trip *k* (Figure 1) the compatibility index is obtained as weighted average with respect to the actual length of the single trip:

$$MCI_k = \frac{\sum_{crossed\ z} MCI^z * l_k^z}{\sum_{crossed\ z}\ l_k^z} \tag{2}$$

with l_k^z the length [km] of trip *k* in zone *z*.

For cities where an FCD sample is available, the adoption of the parametric approach suggested in Nigro et al. (2022) allows the determination of the threshold value of (2) that can imply higher potential of EMM demand shifted from private cars; this corresponds to the value of MCI^z to be assured in each zone of the city to promote EMM (MCI^*).

To derive MCI^*, physical and functional characteristics of the links extracted from OSM are considered. L_m^z required in (1) is composed by cycleways, pedestrian streets, residential streets, some secondary roads, tertiary roads and paved trails. This selection comes from the updated version of the Italian Traffic Laws approved in 2022, which specifies important provisions and new rules for EMM, with particular regard to e-scooters. In urban contexts, EMM can circulate on roads whit a speed limit for motor vehicles up to 50 km/h (i.e. residential streets and some secondary and tertiary roads, with the speed limit for e-scooters set to 20 km/h), on pedestrian areas (with the speed limit set to 6 km/h, excluding sidewalks where e-scooters are not allowed), on mixed pedestrian-cycle paths, on reserved cycle lanes and on cycle priority roads (e.g.

cycleways and paved trails). On extra-urban roads, e-scooters are admitted exclusively on cycleways or other routes reserved for bicycle circulation.

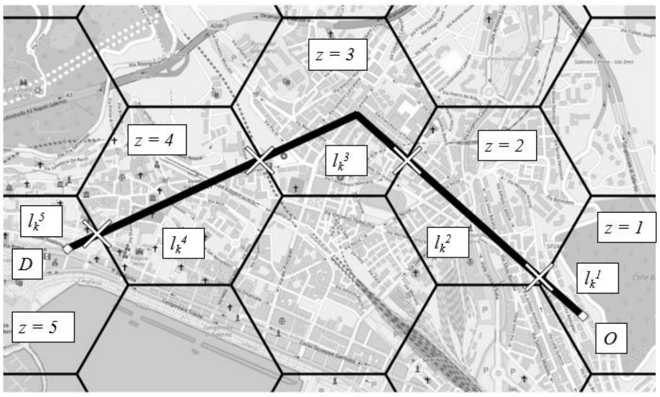


Figure 1: Example of partition of trip *k* in sub-lengths for the computation of MCI_k.

Moving to DS, it measures the number of stops N in a certain zone divided by the area; since the hexagonal zones have all the same area, DS is simply computed as the number of stops (as resulting from GTFS) in each hexagon.

Finally, PTAL is based on the procedure adopted by Transport for London (Authority of Greater London, 2015) that extrapolates the level of accessibility to PT network as a function of the access times (usually walking access, whereas in this case it is modified to account for EMM access) and waiting times (as derived by PT lines frequencies). The computation of PTAL for each hexagonal zone *z* has been conducted as follows:

- Computation of the Access Time of stop *s* from zone *z* (AT_s^z): it is the distance from the centroid of the zone *z* to a certain stop *s* located within the average EMM access distance (considering the same EMM network as defined for the computation of L_m^z), divided by the hypothetical EMM speed (10 km/h according to Castiglione et al., 2022);
- Computation of the Average Waiting Time of stop *s* from zone *z* (AWT_s^z) = 0.5*(T/frequency): the frequency derives from GTFS data considering each route that transits in the time period T through the stop *s* reachable from the centroid of the zone *z*;
- Computation of the Total Access Time of stop *s* from zone *z* (TAT_s^z) = AT_s^z + AWT_s^z;
- Computation of the Equivalent Frequency (EF_s^z) = 0.5 * (TAT_s^z/ T);
- Computation of the Accessibility Index of zone *z* (AI^z): AI^z is function of EFs at each stop *s*, with a higher weight assigned to the stop *s* characterized by the maximum *EF*:

$$AI^z = 1.0 * \, EF_{Max}^z + \, 0.5 \sum_{s \neq Max} EF_s^z \qquad (3)$$

- Accessibility Level of zone *z* (AL^z or $PTAL^z$): it is function of AI using specific thresholds as defined by Transport for London.

2.3. EMM-PT trip, phase 2: accessibility potential to destination by PT, relevant indicators

Commonly, active measures to promote accessibility by PT are mostly related to travel costs and activities location. Hereafter, they were considered through the Weighted Mean Travel Cost from zone z to activities ($WMTC^z$; Gutiérrez and Gómez, 1999) and the Economic Potential from zone z to activities (EP^z; Gutiérrez and Gómez, 1999).

$WMTC^z$ is a location-based accessibility metric. $WMTC^z$ weights the travel cost C_{zj} from the starting zone z to the destination zone j of the study area by the attractive mass M_j:

$$WMTC^z = \frac{\sum_j (C_{zj} * M_j)}{\sum_j M_j} \tag{4}$$

EP^z is defined as an active gravity-based accessibility index. It is directly proportional to the attractive mass M_j (the same variable defined in $WMTC^z$) and inversely proportional to the travel cost C_{zj} to reach all the destinations j of the study area from zone z:

$$EP^z = \sum_j \frac{M_j}{C_{zj}^{\alpha}} \tag{5}$$

where α is a positive parameter emphasizing the impact of the travel cost.

M_j in (4) and (5) can be further specified as a function of the features of PoIs in j, since each activity can impact the accessibility by PT in a different way (e.g. different impact on departure time choice, on number and frequency of visits). At this first stage of the research, since no specific information about the economic impact was available yet, M_j was simply assumed as the number of PoIs at destination j.

The travel cost C_{zj} was related to the travel times by PT defined through the implementation of a Connection Scan Algorithm (Dibbelt et al., 2018), i.e. a timetable GTFS-based algorithm for public transport path search.

2.4. Level of Propensity: definition and validation

A multi-dimensional domain-based has been adopted to classify the zones as a function of their low/high propension to multimodality (specifically, EMM combined with PT).

The multi-dimensional domain depends on the number of explanatory variables considered for ranking this propension. Bearing in mind the indicators defined in the previous sub-sections, specifically related to the access phase by EMM to PT stops ($MCI*$, DS^z, $PTAL^z$) and to the accessibility potential to destination by PT ($WMTC^z$, EP^z), a correlation analysis allowed variables' dependency to be avoided.

Once obtained uncorrelated variables, referring to thresholds recommended in the scientific literature helps in uniquely defining extreme LoP values (in the best case all the explanatory variables exceed the acceptable limits, whereas the worst condition experiences the opposite situation). Assuming the failing of one or more indicators (with respect to recommended thresholds) implies intermediate LoPs that, concurrently, quantify different modal shift potential (the higher the LoP, the more likely the EMM plus PT usage and the lower the car adoption). Since PT demand is generally not available, an indirect analysis was proposed through FCD allowing car adoption to be evaluated. Specifically, the density of generated trips by car DTG^z (i.e. ratio between FCD trip generation g_z, and population of each hexagonal zone z) defines this correlation:

$$DTG^z = \frac{g_z}{pop_z} \tag{6}$$

High density of generated trips, which means higher level of car-usage pro-capita, is expected in zones with low LoPs as a consequence of poor EMM accessibility and/or weak PT service.

The validation process must pay attention to zones with low population (e.g. industrial areas) or to cases where low generated FCD trips are attributable to a low FCD penetration rate (variable on a zone by zone basis).

3. Computation and validation of LoP: the case study of Salerno (Italy)

To check the operation and feasibility of the described methodology, a medium-sized city in the south of Italy (Salerno) was used as test field. Salerno covers around 59 km^2, with about 132,000 inhabitants and 25,000 employees. Its economy mainly focuses on commercial and tertiary sectors. OSM identifies 616 activities in the city divided into categories as follows: 16% shops, 31% amenities, 8% offices, 3% education, 4% tourism, 12% leisure and 26% industrial buildings.
Population, employees and some specific PoIs (shops, offices, amenities, leisure) are mainly located along the coastline, whereas the south of the city constitutes the industrial pole (as depicted in Figure 2) and mostly hosts manufacturing and production buildings; instead, in the northern part of the city it is easier to come across touristic spots, so much so that the port, also located in the north, is a hub not only for commerce, but also for touristic flows (also thanks to its proximity to the Amalfi coast). The hexagonal grid divides the municipality in 209 zones.

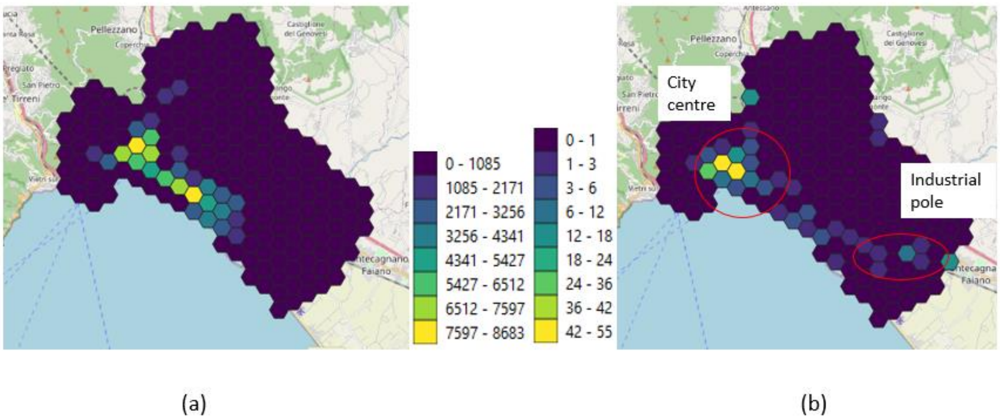


Figure 2: Hexagonal grid and distribution of population (a), PoIs (b) in the municipality of Salerno.

PT service consists of bus lines supplied by the operator Busitalia. In a standard week-day, Busitalia provides 42 bus lines. Stops within the municipality are 697.

Focusing on EMM, Salerno offers an e-bike station-based sharing service with 50 micro-vehicles and 5 bike-stations; bike lanes are approximately 3 km long, concentrated along the coast. Since an e-bike sharing service already exists, e-scooters and bus lines multimodality was the focus of this test field, so as to be able to evaluate through the LoP the potential in the case of additional EMM services. As a consequence, for the computation of $PTAL^z$ according to (3), the e-scooter access distance to stops was set equal to 3 km (McKenzie, 2020), whereas the time period T was assumed as the weekday peak hour 7:30-8:30.

The analysis of the road network highlights a structure potentially suitable for EMM, as suggested by the prevalence of residential streets in the municipality (about 36% according to the OSM classification) and a non-negligible portion of tertiary and secondary roads (12% and 8% of the road network, respectively).

In 2019, from August 31st to October 2nd, Salerno recorded 6.5 million of trips by about 88,000 vehicles (FCD). The application of several filters allowed data outliers to be identified (i.e. recording errors or trips having their starting and/or ending point outside the municipality, so as to consider only internal trips). Specifically, the filtering criteria adopted for exclusion are: travel distance over 100 km, travel times over 2 hours, travel speed over 150 km/h. Moreover, trips of the same vehicle spaced out over time less than 10 minutes have been considered as a unique trip (concatenation procedure). Thus, the final database consists of 176,400 trips by about 7,200 vehicles.

3.1. Results about the access phase by e-scooters to PT stops

According to the parametric approach reported in the literature (Nigro et al, 2022), the availability of Salerno FCD data allows the computation of the MCI_k of each car trip k, as well as the determination of the threshold value MCI^* that implies higher potential in terms of shifting from private cars to EMM.

As depicted in Figure 3, in the case of Salerno increasing the target over 1.0 leads to a collapse in the potential EMM demand, whereas values lower than 0.8 do not determine such significant differences in the potential shifting from private cars to EMM. Consequently, an MCI^* equal to 0.9 was assumed as threshold value for the case of Salerno. Therefore, a zonal MCI^z of 0.9 is the value to be assured in each zone of the city to promote EMM (i.e. zones with MCI^z lower than 0.9 are less e-scooter oriented).

Once computed the MCI^z for all the hexagonal zones of Salerno, their comparison with the target value of 0.9 shows a general low infrastructural propensity to EMM and specifically to e-scooters (Figure 4): the MCI^z mean value is about 0.4 (with a standard deviation equal to 0.42) and its median around 0.28. Zones with adequate values (equal or higher than 0.9) are just 24% of the total ones, but it is worth noting their spatial distribution since they are mainly located in the city area with higher population density, so as to be able to count on a potentially very large user base; indeed, about 79% of the inhabitants live in zones with MCI^z equal or higher than 0.8, that means a much large pool of users prone to change modes of transportation, even if e-scooters would be limited to a confined area. Only 3% of the zones has an MCI^z higher than 1.1 and these are located along the coastline, where the density of road infrastructures and pedestrian streets is higher.

Moving to the PT analysis, the DS indicator is higher along the coastline (Figure 5(a)) consistently with the population density; instead, in the southern industrial pole stops are sprawled, thus decreasing the number of access points to the PT network. Around 48% of the zones have not stops: this implies a low mean value (3.3 stops/hexagon) and a high standard deviation (4.9 stops/hexagon).

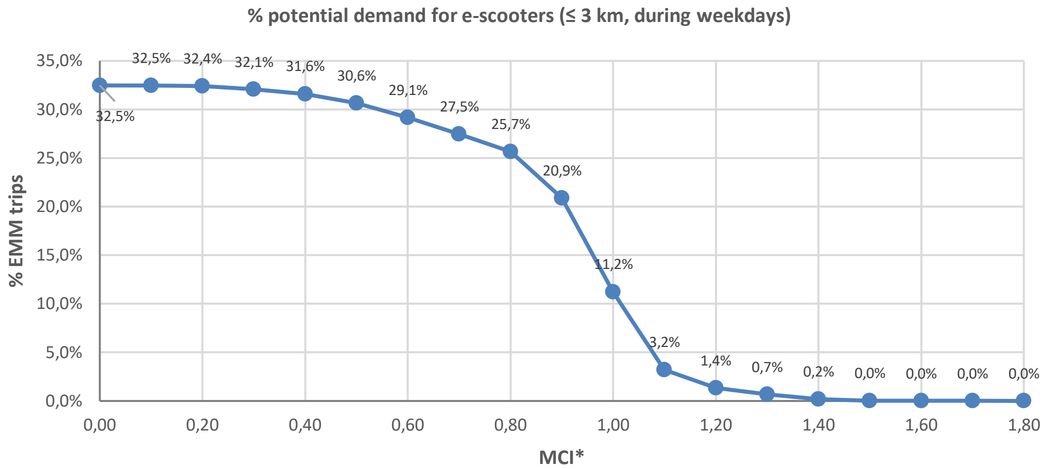


Figure 3: Changes in the potential demand for e-scooters as a function of the threshold value *MCI**.

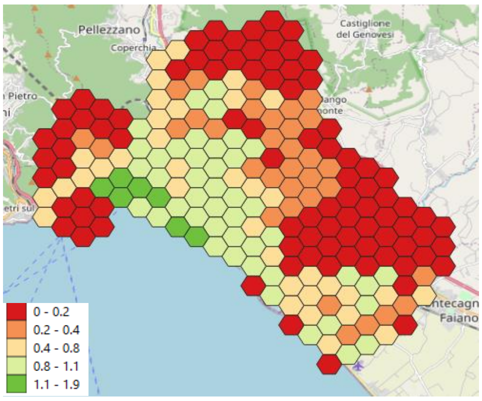


Figure 4: Spatial distribution of MCI^z (Salerno, Italy).

Besides the number (DS), PT stops location is another essential variable impacting PTAL^z (Figure 5(b)): indeed, stops are placed far away from the centroid of each zone and road infrastuctures suitable for EMM are lacking. Zones with an Accessability Index AI^z over the reccomended value of 15 (corresponding PTAL^z level from 4 to 6b, since PTAL^z is a function of AI^z; Wu and Hime, 2003) are around 13%; within the whole municipality, AI^z mean value is about 5.22 (corresponding PTAL^z level 2), with a standard deviation of 9.56. AI^z is equal to 0, i.e. the worst case, in the 51% of the zones.

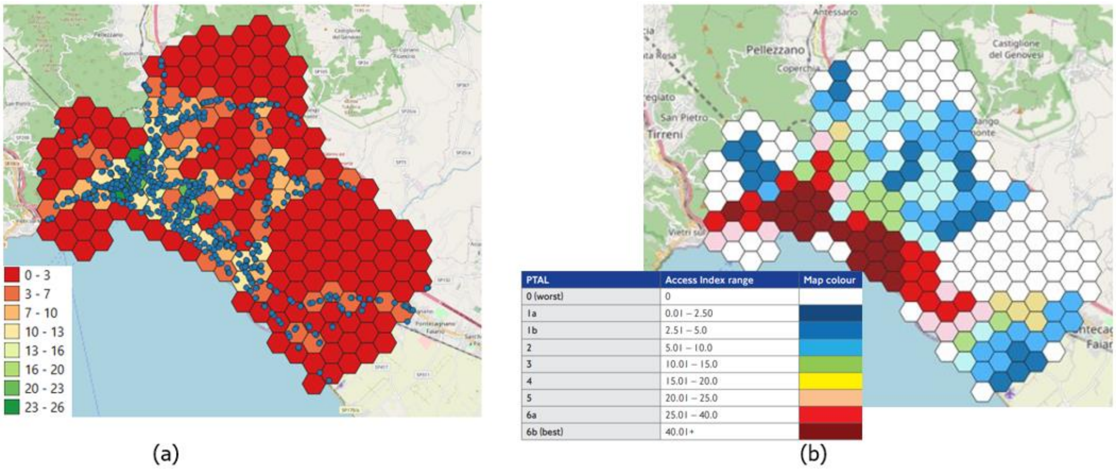


Figure 5: Location of PT stops and spatial distribution of DS (a); PTAL (b) in the city of Salerno.

3.2. Results about the accessibility potential to destination by PT

Total travel times, including access and waiting times, computed on the whole municipality, show a mean value of about 70.8 minutes, with a standard deviation of 32.79 minutes. However, 26% of connections between centroids of the zones does not appear to be covered by PT services, so their travel times are fixed equal to 1'000 minutes for indicators' calculation purposes.

$WMTC^z$ shows low values along the coastline (Figure 6(a)) where population and specific PoIs are concentrated, with half of the total number of hexagons (covering 88.2% of the population) with a value lower than 60 minutes. At the same time, the high attractiveness of PoIs in the southern industrial pole compensates for any longer access and waiting time, so as to result in low weighted mean travel costs also in that area.

EP^z (Figure 6(b)), computed fixing the α parameter of (5) equal to 1, shows high values (over 15 PoIs/minute) in 33% of the zones (covering 83.2% of the population), concentrated along the coastline and in the industrial hub. Analogously to $WMTC^z$, EP^z assumes low performance (low number of reachable PoIs/minute) in the zones uncovered by the PT. Indeed, the Pearson correlation index between EP^z and $WMTC^z$ is equal to -0.84.

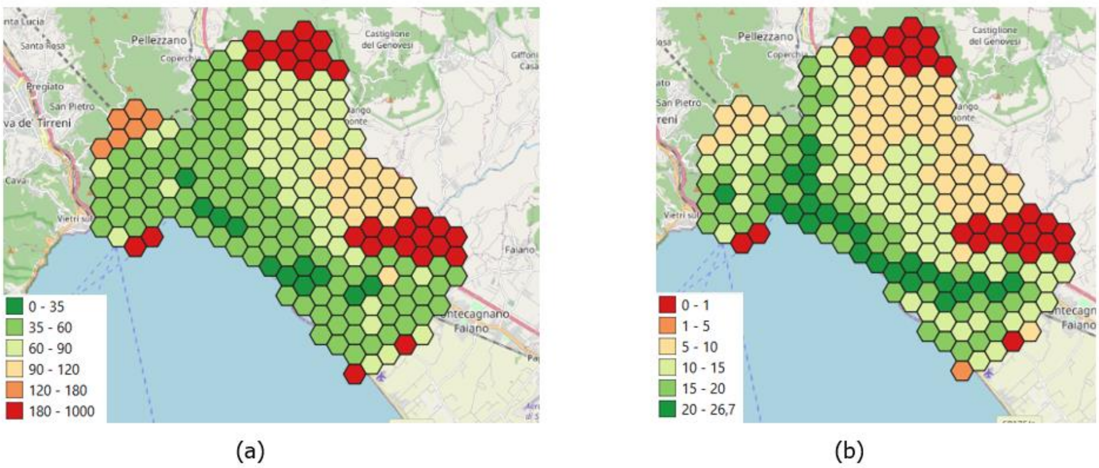


Figure 6: Spatial distribution of $WMTC^z$ (a) and EP^z (b) in the city of Salerno.

3.3. LoP computation and validation

Preliminary, in order to apply the multi-dimensional domain-based classification, the correlation between the previously computed indicators has been verified. As reported in the previous section, EP^z and $WMTC^z$ are highly correlated (Pearson coefficient equal to -0.84); instead, DS^z and $PTAL^z$ did not show high correspondence (Pearson coefficient equal to 0.54). But it is worth noting that $PTAL^z$ partially covers the information about stops distribution through $AT_s{}^z$. Consequently, to avoid overlapping and conflicting information, only $PTAL^z$ was adopted in the analysis. Finally, the multi-dimensional domain included in the elaboration also the index MCI^z, since it is specific to the infrastructural propensity of EMM and it has not any relationship with the other parameters.

The thresholds indicating the condition for high propensity are reported in Table 1: MCI^z threshold value depends on MCI^* that is a city-specific value to be computed case by case (0.9 for Salerno as explained in paragraph 3.1). About the other indicators, according to Wu and Hine (2003) a good $PTAL^z$ is obtained from level 4 (where AI^z starts assuming values higher than 15). The threshold for $WMTC^z$ is a function of the transport mode and the city's urban configuration; the threshold value of 30 minutes reported in Gutierrez and Gomez (1999) for Madrid has been here amplified to 45 minutes considering the different average traffic speed of the city of Salerno (about 20 km/h for cars as derived by FCD, De Vincentis et al., 2022) and the related commercial speed of the bus service (about 12 km/h).

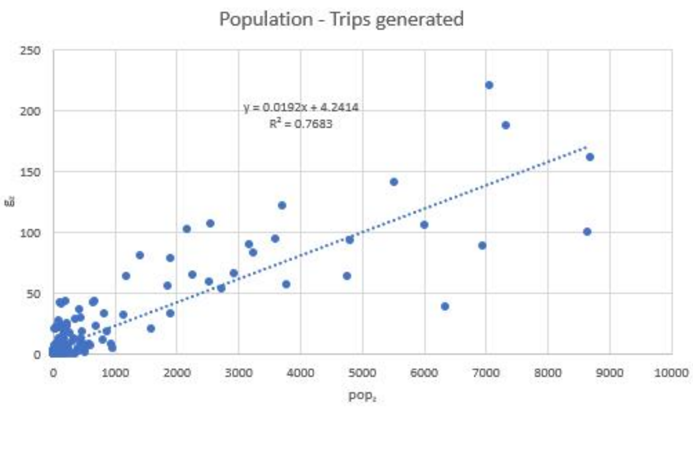
Table 1: Thresholds of the selected explanatory variables.

Metric	*Threshold Value*	*Condition for EMM+PT propensity*
MCI*	0.9	$MCI_z > MCI^*$
PTAL*	4	$PTAL^z > PTAL^*$
WMTC*	45	$WMTC^z < WMTC^*$

The adoption of specific thresholds leads to the definition of unique extreme LoP values (the highest/best LoP will correspond to the conditions: $MCI^z \geq MCI^*$; $PTAL^z \geq PTAL^*$; $WMTC^z \leq WMTC^*$. The lowest/worst LoP will be associated with the exact inverse case). Indeed, most of the real situations will fall somewhere in between. As explained in the methodology section, the procedure adopted for the elaboration was based on comparing the assumption on thresholds for intermediate LoPs with the related modal shift in terms of car adoption (based on DTG^z as specified in (6)).

Generated FCD trips by each zone have been firstly compared to the population distribution in order to verify the sample representativeness, since the procedure can suffer a possible not homogeneous FCD penetration rate (Figure 7 (a)).

Thus, once verified the FCD penetration rate and once computed the DTG^z values (Figure 7 (b)), zones with no population and no trip generation (5 zones in the south-east boundary), as well as zones with not proportional generated trips with respect to the population have been excluded for the definition of intermediate thresholds.



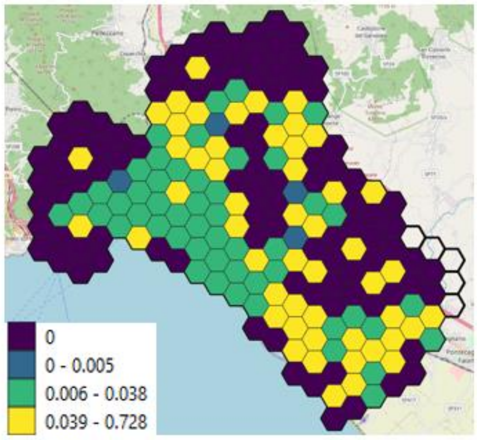


Figure 7: Scatterplot between generated FCD trips and population (a); spatial distribution of DTG^z (b) in the city of Salerno.

Table 2 summarizes the LoP classification, where two additional levels have been identified with respect to LoP A (the best one) and LoP D (the worst one). Figure 8 shows the final validation of these levels by comparing the LoP scale with the corresponding DTG^z: basically, it is verified that zones with lower LoPs have a higher density of trip generation by car.

Table 2. Definition of LoPs.

LoP	*Condition on MCI^z*		*Condition on $PTAL^z$*	*Condition on $WMTC^z$*
A (best)	$MCI^z \geq MCI^*$ (+)		$PTAL^z \geq PTAL^*$ (+)	$WMTC^z \leq WMTC^*$ (+)
B	$MCI^z > MCI^*$ (+)	or	$PTAL^z > PTAL^*$ (+)	$WMTC^z > WMTC^*$ (-)
C	$MCI^z < MCI^*$ (-)	or	$PTAL^z < PTAL^*$ (-)	$WMTC^z < WMTC^*$ (+)
D (worst)	$MCI^z < MCI^*$ (-)		$PTAL^z < PTAL^*$ (-)	$WMTC^z > WMTC^*$ (-)

+ indicates if the condition for propensity is met, – when the condition is not met.

Figure 9 depicts the zones of Salerno in the multi-dimensional domain, as well as their LoP and location: 16 zones, mainly located along the coastline and covering 52% of the population, show a LoP A. In this cluster, the mean accessibility according to $PTAL^z$ is level 6a (the second best one according to the classification of Transport for London), the mean MCI^z is equal to 1.09, the $WMTC^z$ is about 35 minutes. Zones with LoP B are mainly concentrated in the north part of the city (18 zones, 17% of the population) and, on average, are characterized by level 2 for the $PTAL^z$, MCI^z equal to 0.95, $WMTC^z$ around 55 minutes. Zones with LoP C are located immediately behind the coastline and in the industrial pole (31 zones, 16% of the population): $PTAL^z$ reaches level 2, the mean MCI^z is 0.64, the mean value of $WMTC^z$ is closed to the threshold value (about 40 minutes). Finally, 144 zones fall into LoP D (15% of the population) with a level of $PTAL^z$ in the range 0-1a, an average MCI^z of 0.1 and a high $WMTC^z$ (higher than 2 hours). However, as already mentioned, the results (summarized in Table 3) must be interpreted also in the light of the parameter DTG^z. Although the consistency observed between DTG^z and LoP, Figure 8 highlights an extremely higher variance of car adoption (i.e. DTG^z standard deviation) for the zones belonging to LoP

D when compared to the other LoPs. This finding suggests that additional items are probably required to fully describe a low adoption of EMM in combination with public transport, not uniquely related to the built environment, the PT features and the road network peculiarities, but more affected by behavioural aspects of users which are not covered in this paper.

Table 3. Explanatory variables mean values for the city of Salerno.

LoP	*# zones*	*% population covered*	*PTAL^z (level)*	*MCI^z*	*WMTC^z (min)*
A	16	52,0	6a	1,09	35
B	18	17,0	2	0,95	55
C	31	16,0	2	0,64	40
D	144	15,0	0-1a	0,10	> 120

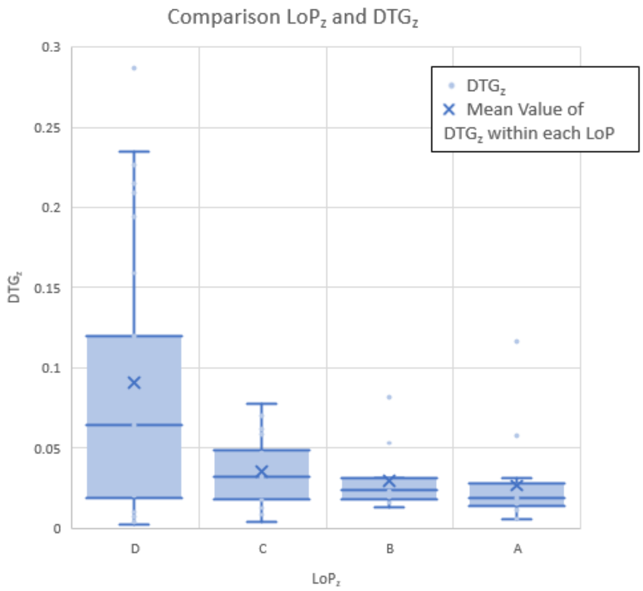


Figure 8: Comparison between LoPs and *DTG^z* for the final classification.

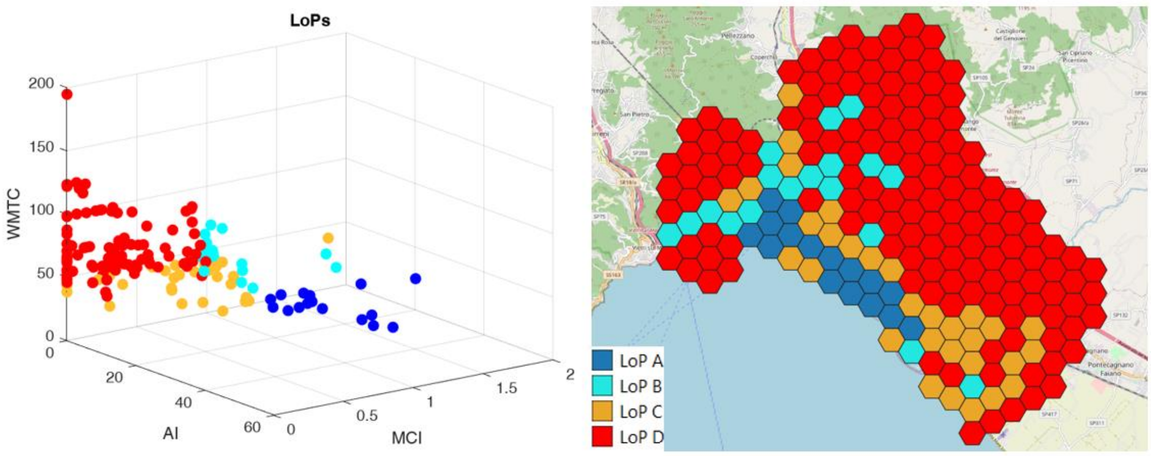


Figure 9: LoP in the multi-dimensional domain and related spatial distribution in the city of Salerno.

4. Conclusion and further developments

In this work a zonal metric, called Level of Propensity (LoP), is proposed for the systemic analysis of multimodality between EMM and PT at urban level. Several indicators have been computed to feed LoP elaboration, using open data regarding the built environment, the PT features and the road network peculiarities. Indeed, LoP is defined according to a multi-dimensional domain-based classification, which combines uncorrelated indicators able to measure the accessibility by EMM to PT stops and the potential accessibility to destination by PT. LoP ranges are finally defined and validated according to their inverse correlation with car adoption.

The city of Salerno was chosen as a test bed for the validation of the proposed methodology, dividing its territory according to a homogenous hexagonal grid used as reference for data analysis and results interpretation. The domain-based classification shows that LoP is mainly impacted by the MCI^z index, which measures the compatibility of the road infrastructures (in terms of road type and road spatial distribution) to EMM: i.e., the higher propensity to multimodality characterizes zones with MCI^z values over its threshold (i.e. MCI* equal to 0.9 for Salerno). Although at a first sight Salerno road network configuration could appear potentially suitable for EMM due to many streets where e-scooters are admitted, the analysis of MCI^z points out an uneven spatial distribution with respect to population density, PT access points and many major activities. This evidence emphasizes the limit of accessibility to PT due to the lack of suitable infrastructures for EMM in certain areas, stressing the need of development strategies for the road network to the advantage of soft mobility, and concurrently demonstrating the importance of a specific analysis based on multi-parameters as the one proposed in this study. The population involved in zones with an MCI^z of 0.8-1 is 62.5% lower than the overall population that involves zones with an MCI^z higher than 1. Consequently, a slight increment on suitable infrastructures for EMM (that would mean higher MCI^z) can lead to a much broader expansion of the catchment area for PT. Moreover, LoP showed how the propensity to multimodality in the municipality of Salerno is negatively impacted by the quality of the PT service, both in terms of frequencies and total travel times.

This research represents a first attempt to define a simple zonal metric able to identify priorities in terms of where/how to improve PT service, where to plan road network developments and how much improvements/efforts in terms of more suitable EMM infrastructures are needed, where to promote mobility hubs enabling easy transfers between PT and EMM.

Further developments of this research could include: i) adapting $PTAL^z$ thresholds to EMM, since $PTAL^z$ is mainly defined for walking access; ii) including availability and fares of EMM in the analysis framework; iii) validating thresholds for LoP in other city contexts where data regarding PT demand are known; iv) tuning MCI^z taking into account also pavement conditions to judge an infrastructure suitable for EMM. Finally, an evaluation of resilience and punctuality of scheduled trips of PT through real-time GTFS could better assess the quality of the service, with positive impact on LoP evaluation.

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