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# Describing Micro-Mobility First/Last-Mile Routing Behavior in Urban Road Networks through a Novel Modeling Approach

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**Abstract:** E-scooters aspire to provide flexibility to their users while covering the first/last mile of a multimodal trip. Yet, their dual travel behavior, i.e., utilizing both vehicles' roadways and pedestrians' sidewalks, creates new challenges to transport modelers. This study aims to model e-scooter riding behavior in comparison to traditional urban transport modes, namely car and walking. The new modeling approach is based on perceived safety that is influenced by the road environment and affects routing behavior. An ordinal logistic model of perceived safety is applied to classify road links in a 7-point Likert scale. The parametric utility function combines only three basic parameters: time, cost, and perceived safety. First/last mile routing choices are modeled in a test road network developed in Athens, Greece, utilizing the shortest-path algorithm. The proposed modeling approach proved to be useful, as the road environment of an urban area is heterogenous in terms of safety perceptions. Indeed, the model outputs show that the flexibility of e-scooters is limited in practice by their low-perceived safety. To avoid unsafe road environments where motorized traffic dominates, e-scooter riders tend to detour. This decision-making process tool can identify road network discontinuities. Nevertheless, their significance regarding routing behavior should be further discussed.

**Keywords:** e-scooter; route choice modeling; perceived safety; first/last mile; road environment

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## 1. Introduction

Micro-mobility has been evaluated as a possible "green" alternative to private cars for door-to-door travelling, contributing to traffic congestion alleviation, noise amelioration, and $CO_2$ emissions reduction [1]. First/last mile trips to/from public transport stations, which are mainly performed by walking, seem to significantly impact the disutility of public transport modes [2]. The term "micro-mobility" was interpreted by the International Transport Forum (ITF) as the use of micro-vehicles: vehicles with a mass of no more than 350 kg (771 lb) and a design speed no higher than 45 km/h [3]. Considering the wide range of vehicles that belong to the micro-mobility group, e-scooters are acknowledged as a suitable solution for urban trips of up to 5 km [4]. An e-scooter is defined as "a wheeled vehicle that: (a) has a center column with a handlebar, (b) is controlled by the operator using accelerator/throttle and brakes, (c) has a foot platform for the operator to stand on, (d) is powered partially or fully by a motor, (e) is manufactured primarily for the transportation of a single person, and (f) it comprises two or three wheels" [5]. E-scooters can cruise at similar speeds to bicycles due to their electric motor, while at the same time they require less road space. Several studies in the USA, Europe, and Asia delineate the popularity of using e-scooters for short-distance trips [6–8], as their combination with public transport may improve the accessibility of urban areas [9]. The considerable increase in the number of e-scooters is attributed to their dual behavior and ability to switch between vehicles roadways and pedestrian sidewalks [10,11]. Due to their flexibility, researchers have been challenged to describe e-scooter routing behavior, while local authorities struggle to properly regulate their use in cities. For example, to date, the use of e-scooters on public highways remains heavily restricted in the UK, with only rented e-scooters allowed, as part of government-approved trial schemes, while privately-owned ones are banned [12].

Although e-scooter users can switch from walking to vehicle usage and vice versa at any moment, previous studies noticed a tendency for using particular infrastructure sections. For instance, a survey revealed that 59% of e-scooter users in Virginia, USA, were willing to change their route to use bike lanes, 29% to follow shared-space roads, 21% to use one-way roadways, and 15% to utilize tertiary roadways, while avoiding on-road vehicles and pedestrians [13]. On the other hand, Zou et al. [14], in their study in Washington D.C., USA, noticed that a high share of e-scooter trips was performed on arterial roads with high traffic volumes and that riders preferred to use bike routes to increase their safety, particularly at night. Ma et al. [15] concluded that speed and vibrations are related to the road environment (i.e., driving on the sidewalk, using the bike lane, etc.), the pavement condition, the slope, and the presence of obstacles. Furthermore, experienced cyclists are more aware of traffic regulations and have a higher risk of awareness [16] as opposed to e-scooter riders who appeared more confused [17]. Cyclists tend to prefer quiet side roads, residential streets, and green spaces/vegetation in order to avoid motorized traffic [18]. Yang et al. [19] found that the most common locations of e-scooter accidents were roads, intersections, and sidewalks, while the 42.9% of the accidents that occurred during the night involved at least one death, compared to the 30.4% of those that occurred during the daytime. Bai et al. [20] performed a comparative analysis between bicycle and e-scooter drivers' perceptions by using ordered probit regression models and concluded that bicycle drivers present higher comfort levels compared to e-scooter riders.

Interestingly, the most notable advantage of micro-mobility modes (i.e., the flexibility) is simultaneously their biggest disadvantage, and indeed, research has revealed some reluctance by e-scooter users and authorities towards increasing e-scooter use on perceived safety grounds [21,22]. In less-organized road environments, which mainly appear in developing countries, micro-mobility users tend to share small spaces with motorized traffic, leading to more frequent unsafe interactions [23,24]. Perceived safety seems to be a catalytic factor, which may determine whether the coexistence of traditional (e.g., car, walking) and new urban transport modes (e.g., e-scooter) may be feasible [25]. Indeed, safety perceptions are hypothesized to be influenced by the existence of high pedestrian flows and static obstacles [26]. Regarding traditional urban transport modes, Kaparias et al. [27] examined pedestrians' and car drivers' safety perceptions in a shared space road environment; the results showed that vehicle traffic, the provision of safe zones, lighting level, age, and gender were among the most significant variables. Feelings of safety or unsafety seem to affect the attractiveness of e-scooters, especially regarding the micro-mobility model, to cover the first/last mile of a trip [28]. Even the satisfaction and loyalty of public transport users are found to be related to traffic and crime safety perception, mainly at public transport stops and cycling/walking routes, as the study of Park et al. [29] highlights.

Studies that attempted to plan micro-mobility networks monothematically focused on the determination of the sharing the location of systems or dockless vehicles, so that door-to-door travel with minimum operational cost is ensured [30–33]. Other works considered micro-mobility networks as part of a multimodal transport network; their approach objected to increasing network connectivity and coverage [34,35]. Yet, a limited number of studies take the road environment into account. For example, the study of Feng et al. [36] utilized big data to model micro-mobility routes; they followed a deterministic all-or-nothing approach, where all e-scooter riders choose the shortest or the simplest path. Significant deviations between the model outputs and real traffic flow measurements were observed, proving that e-scooter riders tend to detour to avoid certain street sections, which are unsuitable or unsafe. The study of Castiglione et al. [37] integrated perceived safety into binomial models that describe the willingness of people to become crowd shippers using an e-bike or e-scooter for their deliveries. Based on their approach, subjective safety relates to the intention of road users to use or not use micro-mobility modes in mixed traffic conditions. Their survey results proved the statistical significance of this additional parameter. The study by Nigro et al. [38] developed a parametric modal shift model using floating car data coming from 240,000 monitored vehicles circulating in Rome, Italy. This novel algorithm searched for car trips that could be substituted by micro-mobility in the future considering three main criteria: travel distance, road infrastructure suitability, and proximity of origin point to public transport stations. The model exploits spatial data from OpenStreetMaps in order to define traffic zones with bike lanes and residential streets with low traffic flows or speeds.

Considering the meso- and micro-scale, Meister et al. [39] attempted to model the route choices of cyclists in a specific traffic zone. Their approach was based on the value-of-distance (VoD), which refers to how much additional distance a cyclist is willing to cycle in order to experience more/less of a certain attribute of the road network, e.g., bike path, bike lane, 30 km/h speed limit, etc. A binary mixed logit model was developed to address this issue both for conventional bicycles and e-bikes. One problematic point of using discrete choice models in modeling routing behaviors is the fact that the alternative paths included in the choice set are not independent. In dense urban road networks, there are serious overlaps [28,39]. This is why the study by Narayan et al. [40] utilized an agent-based model (i.e., MATSim) to propose a multimodal route choice model that considers first/last mile transport to/from public transport stations. The developed utility function contains variables related to access, egress, transfer, in-vehicle time, and cost. One limitation of this approach is that the framework of MATSim utilizes a teleportation algorithm to simulate active mobility trips, i.e., agents' relocation from the trip origin to the destination with a time delay based on transport mode speed and the Euclidean distance [28,41]. The approach of Ziemke et al. [42] recommended the inclusion of additional factors, i.e., road infrastructure, comfort, gradient and travel delay, due to interactions with other road users, to better score and simulate bicycle trips in an agent-based model.

This study combines the previously mentioned approaches and aspires to propose a more universal modeling approach by utilizing perceived safety as a key parameter to describe e-scooter riding behavior in comparison to traditional urban transport modes, namely: car and walking. As perceived safety is related to the road environment, the model encloses all these relevant design parameters which determine the supply of the road network and impact on the first/last mile route choices. Perceived safety is also utilized to describe the heterogeneity appearing in the road environment that negatively influences the comfort, especially of e-scooter riders. The proposed approach is based on a new parametric utility (or cost) function that contains only three basic variables: trip time, cost, and perceived safety. This novel utility function is designed to be adjustable to different modeling or simulation frameworks, e.g., discrete choice models; agent-based models, such as MATSim; and trip assignment algorithms. In this study, the shortest path algorithm is updated in order to identify differences in routing patterns per mode in an experimental road network that is developed for central Athens, Greece. The overall performance and the outputs of the proposed model are assessed and discussed by importing various parameter settings and road network scenarios. The paper is structured as follows: in Section 2 the modeling approach is presented, followed by a description of test scenarios in Section 3, the results in Section 4, and finally, the discussion and conclusions are provided in Sections 5 and 6, respectively.

## 2. Modeling Approach

This study hypothesizes that perceived safety acts as an intermediate parameter that is influenced by the road environment [43–45] and affects route choices. In other words, first/last mile travelers search both for the shortest and the safest path to reach their destination [46]. Based on this hypothesis, the shortest path algorithm is updated considering utility estimations and modes as the weight of each link.

Figure 1 presents an overview of the modeling approach. In essence, it combines two prediction models. This approach has been followed in the past for modeling the willingness of air travelers to pay for safety improvements [47] and the driving stress of tram drivers [43]. The first model is an ordered logit model that estimates the perceived safety level per link and per transport mode based on road environment parameters, which are presented in the next paragraph. The second one models route choice behavior based on a new parametric utility function. The utility function is based on the value-of-distance or safety approach also followed in the study by Meister et al. [39]. Road links and their attributes are the main inputs (i.e., spatial data inputs) of this modeling process; the model outputs refer to a set of paths from the selected origin to the destination per transport mode. The overall approach is called the Perceived Safety Choices model; Psafechoices is an open-access package (i.e., free software with MIT license) programmed in python that was developed at the National Technical University of Athens. It is available online (Perceived Safety Choices Model: https://github.com/lotentua/Perceived_safety_choices (accessed on 7 September 2022)).

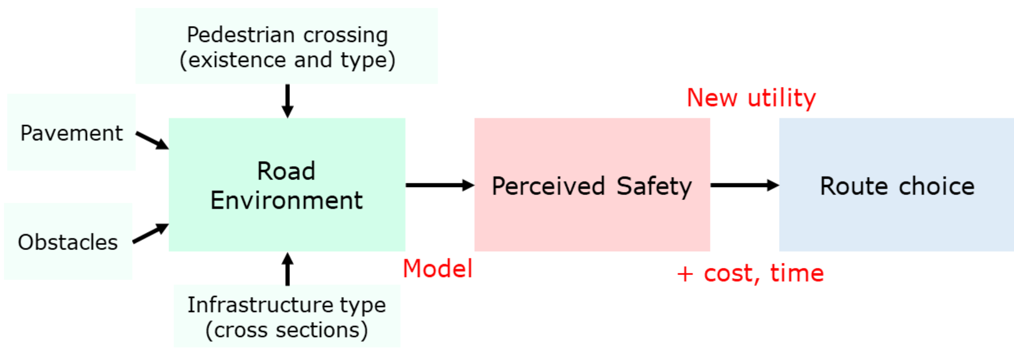



**Figure 1.** The "Perceived Safety Choices" model: a combination of an ordered logit perceived safety model and a new utility (or cost) function.

### *2.1. Perceived Safety Model*

Perceived safety is a subjective notion that refers to the individual safety perceptions regarding the occurrence of a serious crash while using a particular transport mode [43,48]. It has been used in some previous studies to describe driving behavior both at tactical or operational level [43,44,48–50]. In this study, perceived safety is modelled for each transport mode that can be used for first/last mile trips. The transport modes, considered in this analysis are car, e-scooter, and walking.

The Likert scale is used to quantify the subjective variable of safety and develop prediction models. A Likert scale from 1 (very unsafe) to 7 (very safe) is used (see Figure 2). This choice is based on previous studies which preferred 7-point Likert scales in order to examine subjective notions of transport safety, such as the perceived safety of tram drivers [43], airline safety [47] and stress of car drivers [51]. Indeed, a 7-point Likert scale provides enough options to effectively capture the respondents' views [52]. These scales use numbers in order to measure preferences and perceptions; yet, they do not actually provide metric information [53,54]. This is because in an ordinal scale the real distance between levels is not the same; therefore, the use of thresholds to configure intervals per safety level is necessary [55]. Perceived safety as an ordinal variable is usually modeled by the use of the ordinal logistic regression method, where kappa thresholds are additional unknown parameters that should be estimated at the end of the process.

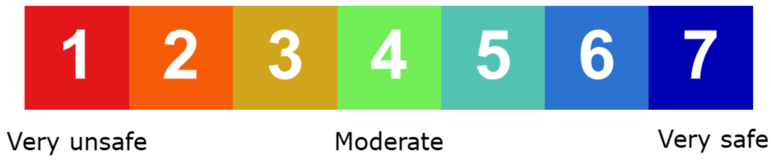



**Figure 2.** Perceived safety Likert scale and colors.

The independent variables are related to the road environment, including infrastructure type, pavement condition, and the existence or non-existence of static obstacles and pedestrian crossings. The model uses four different types of cross-sections to classify urban roads.

These designs are:

- type 1: urban road with sidewalk <1.5 m wide and without a cycle lane;
- type 2: urban road with sidewalks ≥1.5 m wide and without a cycle lane;
- type 3: urban road with a cycle lane;
- type 4: shared space (or traffic calming zone)

Therefore, type 3 describes a case where traffic flows are fully segregated, while type 4 refers to a case where the urban road space is shared by all road users [56,57]. To mix or to segregate traffic flows is one of the main dilemmas that experts face; this was revealed by the literature review on transforming concepts of urban spaces conducted by Tsigdinos et al. [58]. Type 1 and type 2 refer to typical cases, where motorized traffic is prioritized, while dedicated infrastructure for cyclists and e-scooter users is absent. Simultaneously, a relatively bad pavement condition seems to increase vibrations when using an e-scooter [15]. Therefore, the pavement condition becomes an additional variable. The walkability of roads may be affected by the existence (or non-existence) of pedestrian crossings in each segment. In this study, two types of pedestrian crossings are introduced: signalized and non-signalized. Obstacles, which are non-moving objects and exist mainly on the sidewalk, may particularly influence the perceived safety of pedestrians or e-scooter users, who tend to adhere to dual riding behaviors (e.g., changing from pedestrians to drivers and vice versa) [11].

As the independent variables related to the road environment are categorical and not continuous, dummy coding schemes are used to describe the potential non-linearities that exist between categories [59,60]. Considering the above, the general model equations are formulated as follows:

$$psafe^{\lambda}_{i,\,\mathrm{m}} = \sum_{j=1}^{4} \beta_{inf\mathrm{j},\mathrm{m}} * \underset{(\mathrm{j})}{inf\mathrm{I}} + \sum_{j=1}^{2} \beta_{cs\ \mathrm{j},\ \mathrm{m}} * csr_{(\mathrm{j})}\,I\mathrm{i} \ + \beta_{pav,\mathrm{m}} * pav\ \mathrm{i} + \beta_{obs,\mathrm{m}} * obs\ \mathrm{i} \quad (1)$$

$$psafe_{i,\,\mathrm{m}} = \begin{cases} 1, & -\infty < psafe^{\lambda}_{i,\mathrm{m}} \le k_{1,\mathrm{m}},\ very\ unsafe \\ 2, & k_{1,\mathrm{m}} \le psafe^{\lambda}_{i,\mathrm{m}} \le k_{2,\mathrm{m}} \\ 3, & k_{2,\mathrm{m}} \le psafe^{\lambda}_{i,\mathrm{m}} \le k_{3,\mathrm{m}} \\ 4, & k_{3,\mathrm{m}} \le psafe^{\lambda}_{i,\mathrm{m}} \le k_{4,\mathrm{m}} \\ 5, & k_{4,\mathrm{m}} \le psafe^{\lambda}_{i,\mathrm{m}} \le k_{5,\mathrm{m}} \\ 6, & k_{5,\mathrm{m}} \le psafe^{\lambda}_{i,\mathrm{m}} \le k_{6,\mathrm{m}} \\ 7, & k_{6,\mathrm{m}} \le psafe^{\lambda}_{i,\mathrm{m}} < +\infty,\ very\ safe \end{cases} \quad (2)$$

where:

$psafeI^{\lambda}_{\mathrm{i},\,\mathrm{m}}$: the latent variable of the perceived safety of using mode m (i.e., car, e-scooter, walk) in liIk *i*;

$psIfe_{i,\mathrm{m}}$: perceived safety level of using mode m in Iink *i* (from 1 to 7);

$k_{1,\mathrm{m}},\ k_{2,\mathrm{m}}, \ldots\ldots k_{6,\mathrm{m}}$: kappa thresholds for mode m; determination of perceived safety level;

$\beta_{inf\mathrm{j},\mathrm{m}}, \beta_{cs\ \mathrm{j},\ \mathrm{m}} \ldots, \beta_{obst,\mathrm{m}}$: beta parameters of (dummy) road environment variables; they differ per mode;

A description of the dummy road environment variables follows:

$\underset{(1)}{inf}\mathrm{i} = 1$: if there is an urban road with sidewalks less than 1.5 m wide but without a cycle lane in link i (infrastructure type 1);

$\underset{(2)}{inf}\mathrm{i} = 1$: if there is an urban road with sidewalks more than 1.5 m wide but without a cycle lane in link i (infrastructure type 2);

$\underset{(3)}{inf}\mathrm{i} = 1$: if there is an urban road with a cycle lane in link i (infrastructure type 3);

$\underset{(4)}{inf}\mathrm{i} = 1$: if there is a shared space road environment in link i (infrastructure type 4);

$csr_{(1)}\ \mathrm{i} = 1$: if there are (zebra) pedestrian crossings not protected by traffic lights in link i;

$csr_{(2)}\ \mathrm{i} = 1$: if there are (zebra) pedestrian crossings protected by traffic lights in link i;

$pav\ \mathrm{i} = 1$: if the pavement of the urban road is in a good condition (i.e., no cracks or dangerous spots, the low frequency of vibrations while riding/cycling) in link i;

$obs\ \mathrm{i} = 1$: if there are obstacles on the sidewalk of the urban road in link i.

A rating experiment is required to estimate the unknown model parameters presented above. In the repository of the perceived safety choices model, survey design, data processing and analysis methods, and tools are provided in order to calibrate this model for each city based on road users' perceptions. This study utilizes parameters, which were estimated by an image-based double-stated preference experiment conducted in Athens, Greece, with 129 respondents [61]. Each respondent evaluated the perceived safety of car driving, walking, and e-scooter riding in 12 hypothetical scenarios, which presented different road environments (4644 perceived safety ratings). Equations (3)–(5) give the calculated models (one per transport mode), based on which the perceived safety of urban road links is evaluated later in the analysis.

$$\begin{gathered} psafe^{\lambda}_{i,\,\mathrm{car}} = -0.510 * \underset{(1)}{inf}\mathrm{i} - 0.450 * \underset{(2)}{inf}\mathrm{i} + 0 * \underset{(3)}{inf}\mathrm{i} - 0.557 * \underset{(4)}{inf}\mathrm{i} - 0.500 * csr_{(1)}\ \mathrm{i} + 0.044 * csr_{(2)}\ \mathrm{i} + 1.006 * pav\ \mathrm{i} \\ +0.178 * oIbs\ \mathrm{i}, \\ with\ k_{1,\mathrm{car}} = -4.310,\ k_{2,\mathrm{car}} = -2.995,\ k_{3,\mathrm{car}} = -2.150,\ k_{4,\mathrm{car}} = -0.872,\ k_{5,\mathrm{car}} = +0.307,\ k_{6,\mathrm{car}} = +1.570 \end{gathered} \tag{3}$$

$$\begin{gathered} psafe^{\lambda}_{i,\,\mathrm{escooter}} = -3.072 * \underset{(1)}{infi} - 2.387 * \underset{(2)}{inf}\mathrm{i} + 0 * \underset{(3)}{inf}\mathrm{i} - 1.899 * \underset{(4)}{inf}\mathrm{i} - 0.290 * csr_{(1)}\ \mathrm{i} + 0.017 * csr_{(2)}\ \mathrm{i} \\ +0.662 * pav\ \mathrm{i} + 0.361 * obs\ i, \\ \text{with } k_{1,\mathrm{escooter}} = -3.452,\ k_{2,\mathrm{escooter}} = -1.9687,\ k_{3,\mathrm{escooter}} = -1.201,\ k_{4,\mathrm{escooter}} = -0.245, \\ k_{5,\mathrm{escooter}} = +0.704,\ k_{6,\mathrm{escooter}} = +1.845 \end{gathered} \tag{4}$$

$$\begin{gathered} psafe^{\lambda}_{i,\,\mathrm{walk}} = -1.621 * \underset{(1)}{inf}\mathrm{i} - 0.547 * \underset{(2)}{inf}\mathrm{i} + 0 * \underset{(3)}{inf}\mathrm{i} - 0.231 * \underset{(4)}{inf}\mathrm{i} - \\ 1.097 * csr_{(1)}\ \mathrm{i} + 0.028 * csr_{(2)}\ \mathrm{i} + 0.183 * pav\ \mathrm{i} + 0.731 * obs\ \mathrm{i}, \\ \text{with } k_{1,\mathrm{walk}} = -4.901,\ k_{2,\mathrm{walk}} = -3.537,\ k_{3,\mathrm{walk}} = -2.709,\ k_{4,\mathrm{walk}} = -1.573,\ k_{5,\mathrm{walk}} = -0.645,\ k_{6,\ \mathrm{walk}} = +0.687 \end{gathered} \tag{5}$$

### *2.2. First/Last Mile Routing Model*

Deterministic shortest-path algorithms, such as the Dijkstra algorithm [62], can define the shortest or the fastest (if a travel speed per link is provided) path from the origin, O, to the final destination, D. Several versions of this algorithm have been applied in the literature [63,64]. By estimating the perceived safety per link and per transport mode, the safest path can be defined. Nevertheless, this process should be constrained by the travel distance; otherwise, the selected safest path can become unrealistically long. Therefore, the perceived safety variable incorporates a distance reference.

Time and cost are (positively) correlated with the distance of the selected path (Equation (6). In order to develop a utility (or cost) function per transport mode, the travel time and trip cost are expressed as a function of distance. A constant travel speed is assumed per link, while delays due to traffic congestion are not considered in this study.

The magnitude of the perceived safety parameter is given by (a) the beta parameter and (b) the ratio of link distance ($d_i$) over the maximum-acceptable unsafe distance ($d_{max}$), after which the perceived safety significantly increases (or decreases) the utility of traveling from the link i. The lower the $d_{max}$ parameter, the higher the magnitude of perceived safety in the utility of link i. For example, some travelers may not accept an unsafe distance of 100 m in their paths; they may detour to avoid this small segment. Of course, this is related to individuals' familiarity with using each transport mode [43] but also to the existence of unsafe (small or large) discontinuities, which may be proven enough to downgrade overall transport utility [65–67]. It is a parameter that should be calibrated. At this point, it should be mentioned that safety scores below 4 decrease the link utility (or increase the link cost). Considering the above, the utility is formulated as follows:

$$U_{\mathrm{m,i}} = \beta_{time,\ \mathrm{m}} * \frac{d_{\mathrm{i}}}{v_{\mathrm{m}}} + \beta_{cost,\ \mathrm{m}} * cd_{\mathrm{m}} * d_{\mathrm{i}} + \beta_{psafe,\mathrm{m}} * (psafe_{i,m} - 4) * \frac{d_{\mathrm{i}}}{d_{\max}} \tag{6}$$

where:

$U_{m,i}$: utility of using mode m (i.e., car, e-scooter, walk) to travel through thI link i;

$\beta_{time,m}, \beta_{cost,m}, \ldots, \beta_{psafe,m}$: beta parameters of utility function; they differ per mode;

$d_i$ : distance If link i in km;

$v_m$ : travel speed of mode m in km/h; it is assumed to be fixed per link;

$cd_m$ : cost per kilometer of using mode m in euros; it is assumed to be fixed per link;

$pIafe_{i,m}$ : perceived safety level of using mode m to traveI through i;

$d_{max}$ : maximum-acceptable unsafe distance in kilometers, after which perceived safety has a significant impact on the utility of using mode m to travel througI the link i (negative impact if $I < 4$; positive impact if $psafe_{i,m} > 4$, no impact if $psafe_{i,m} = 4$).

Another issue which has to be discussed is whether a link with low safety score should be included in the road network. It is questionable whether road users can really use very unsafe ("dangerous") routes to travel from point O to D. This is related to the acceptability of each individual to follow unsafe paths, thus limiting transport supply. Hence, the minimum-acceptable perceived safety level (minv) is related to the confidence of one road user to use the transport mode (m) in less safe links (i) that exist in the road network [39]. Based on this approach, the connectivity and supply of road networks is influenced by safety perceptions.

A framework for calibrating such a model is provided in the online repository (see the link on page 3). In practice, the model calibration is based on a binary logistic regression calculation process, which is performed per transport mode. Responses collected from the stated preferences experiment conducted in Athens are utilized in this study [61]. The value of time when driving a car and riding an e-scooter are estimated to be 8.20 and 5.68 EUR/h, respectively. The trip cost of walking is fixed to zero, while the cost of car driving is set 0.15 EUR/km. The cost of e-scooter riding is estimated to be 0.46 EUR/km considering a sharing micro-mobility service with an hourly cost of EUR 7 (EUR 1 for unlocking). In this analysis, the travel speed is constant per link and equal to 40, 15, and 5 km/h for the car, e-scooter, and walking, respectively. Regarding the value of safety (VoS), based on the collected responses, it is equal to −12.73 min/safety level for e-scooter riding. This means that e-scooter users are willing to exchange one safety level for 12 min of less travelling. The value of safety is equal to −9.08 min/safety level for car driving and −8.69 for walking.

## 3. Test Scenarios and Data

The developed routing model is first applied in an experimental scenario developed in the Athens, Greece, downtown area. The purpose of this setup is to investigate routing patterns, considering trip distances under 10 km. The study area is within the municipality of Athens. According to the 2021 census, the population of the municipality is equal to 637,798 inhabitants (results of a population census in Greece: https://elstat-outsourcers.statistics.gr/Census2022_GR.pdf (accessed on 7 September 2022)). The study area includes Athens' commercial triangle where shops, hotels, restaurants, etc., are concentrated. In addition, ministries and public services can be found around Syntagma Square and Panepistimiou Avenue. Therefore, the study area attracts many daily trips.

The road network mostly consists of narrow (one way) streets and pedestrianized zones, which hinder the use of private cars. As an alternative, there are six metro stations and two tram stations, which support the trips to/from the city center of Athens making public transport the most efficient and therefore the most attractive option for visiting the area. Available travel demand data in the study area show that around 96.2% of access/egress trips are performed by walking (i.e., September 2022). This is related to the travel patterns appearing in Athens, where only 1.95% of trips of 5 km or less are undertaken by bicycles or e-scooters [68]. The development of a metropolitan cycle network, which will connect the city center of Athens with the other municipalities has been discussed in previous studies [69,70]; unfortunately, only a small fraction of it has been constructed.

For building the routing model, a road network of 257 nodes and 400 links was constructed. Figure 3 presents the study area and the experimental road network. To perform meaningful comparisons in the routing patterns, pedestrianized streets were excluded from the analysis. Some exceptions to this are Aiolou Street and the route from Dion. Aeropagitou and Apost. The Pavlou street, which comprises a wide, 1.38 km-long pedestrianized route that connects the Acropolis of Athens with the Ancient Market. Indeed, its width allows the coexistence of pedestrians with cyclists and e-scooter riders. In the developed network, there are no cycle lanes, with the exemption of the Vas. Olgas and Panepistimiou Avenues, where pop-up cycle lanes were established during the lockdown of May 2020, during the COVID-19 pandemic [53,71]. Of the road network links, 76.8% are one-way. For simplicity, only nine external zones are specified. These zones are connected with the established road network via a single one-directional link. The transport demand is not modeled, since the study focuses on the examination of routing first/last mile routing behavior. Therefore, trips are only considered from zone 9000 (as indicated with a red circle in Figure 3) to zone 4000 (indicated with a green circle in Figure 3). An all-or-nothing (AON) routing strategy is followed; this means that all travelers starting from the origin select the best alternative path in order to travel to their final destination.

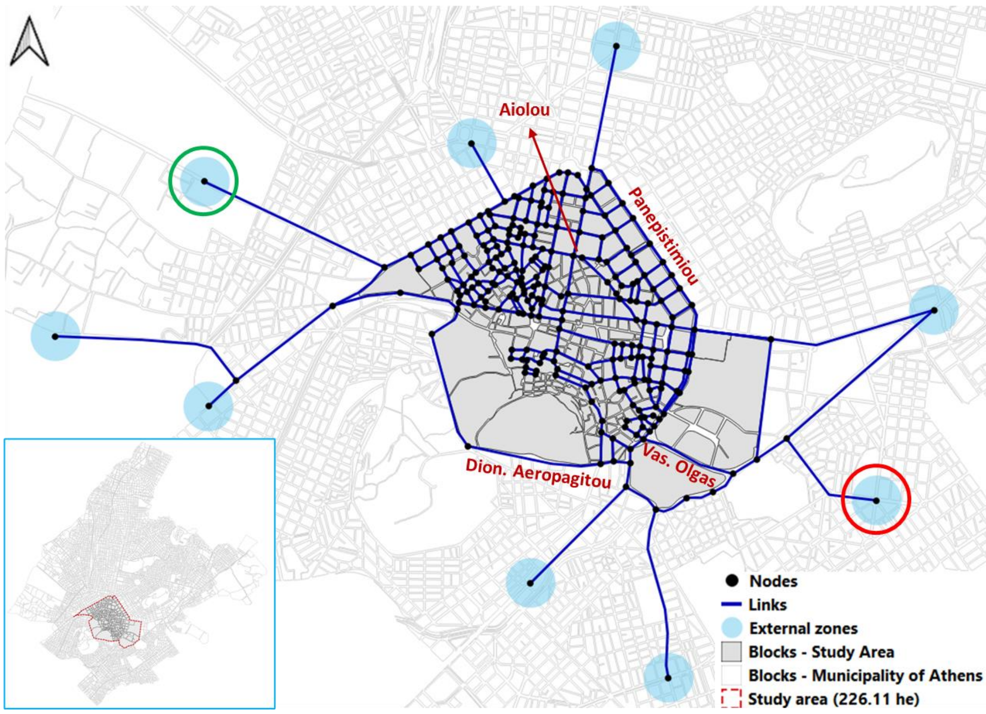
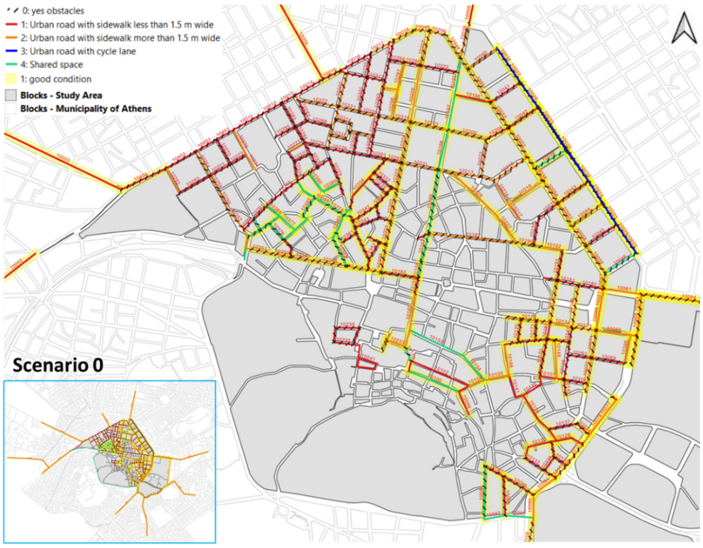
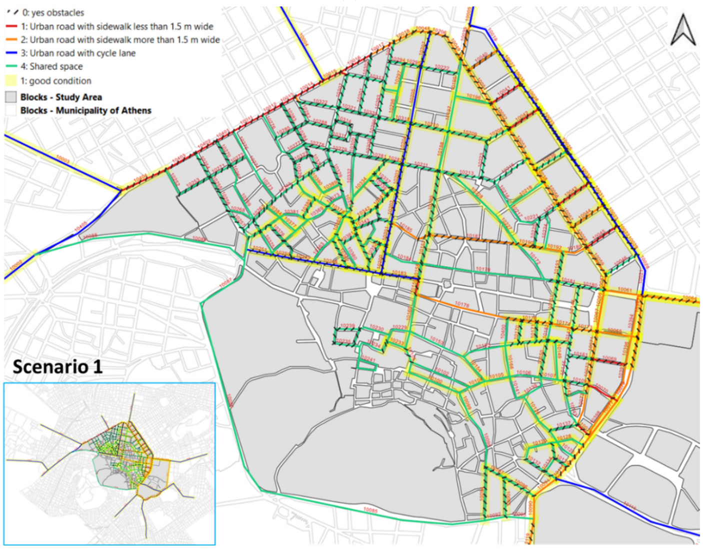



**Figure 3.** Study area and road network (the small map shows the municipality of Athens, Greece).

Scenario 0 gives the present situation of the road network. It was created by collecting various spatial data related to the existence or not of cycle lanes, sidewalk width, speed limit, pavement conditions, the presence of obstacles, and pedestrian crossings. In addition, photographs collected from the field are utilized in order to fill or update the dataset with new information. To estimate perceived safety, the modeler ought to describe the road environment using the variables presented in Equation (1), following pre-defined specific classifications. The infrastructure type is described by the following tags: "1: Urban road with sidewalk less than 1.5 m. wide", "2: Urban road with sidewalk more than 1.5 m. wide", "3: Urban road with a cycle lane", and "4: Shared space". By observing the photographs, the modeler can judge the pavement condition using the following tags: "0: bad condition" and "1: good condition", while the existence of an obstacle is given by the next classifications: "0: yes obstacles" and "1: no obstacles". Last, the existence and the type of pedestrian crossings per links are imported by three specific levels: "0: without pedestrian crossings", "1: with pedestrian crossings not controlled by traffic lights", and "2: with pedestrian crossing controlled by traffic lights". By using a geographic information system (GIS), the data are imported and organized in a single shapefile, which gives the attributes of each link in the road network. Figure 4a shows the current status of the road network.




(**a**)




(**b**)

**Figure 4.** Presentation of (**a**) Scenario 0 and (**b**) Scenario 1.

This standardized shapefile can also be utilized to plan new scenarios and assess their potential to facilitate first/last mile travelling using micro-mobility modes. In this study, Scenario 1 is created for this purpose. Scenario 1 is based on a strategic road network formulation with specific hierarchical levels that were first developed by Tsigdinos and Vlastos [72]. This new hierarchy prioritizes active modes in the streets of the city center of Athens. Respecting this hierarchy, traffic calming measures in the form of shared space are planned in the inner-road network, while multimodal corridors with specialized cycling infrastructures are introduced in the main arterial routes [73]. Lastly, in Scenario 1, cycle lanes are established in the Athinas and Ermou streets, completing the cycle network of the city center. The changes in the road environment proposed for Scenario 1 are shown in Figure 4b.

## 4. Results

The results are exported by applying the algorithms of the perceived safety choices model. As has been mentioned, collected spatial data are organized in shapefiles, which are imported to the perceived safety calculator; the safety estimations are exported in a .csv file that is used (a) to create maps of safety evaluations and (b) to search for alternative paths via the routing model. Ultimately, the alternative paths are defined using a sequence of nodes.

Starting with the evaluation of perceived safety, Figure 5 illustrates the results per transport mode. A relatively small percentage of links (i.e., 0.4%) reaches level 6 for safe e-scooter use; this corresponds to a 5.84 km network length and mainly refers to segments where pop-up bike lanes have been established. Additionally, the perceived safety to ride an e-scooter equals level 2 (i.e., just one level above 1, which corresponds to very unsafe situations) in 57.78% of links. On the other hand, the car-driving subjective safety of 48.89% of links is rated as level 6. The minimum safety score for car driving is equal to 4, while walking is equal to 3. It is noticeable that for pedestrians, 27.8% of links are grouped into level 4, followed by 21.41% of links at level 5. Yet in Scenario 1, the perceived safety of walking is improved. He outputs of this analysis show that approximately 89% of links score at level 6 or higher; this corresponds to a road network of 55.93 km, which is perceived as very safe. Scenario 1 seems to balance the perceived safety evaluations of e-scooter riding as well. Indeed, 62.22% of the links reach level 3 and 6.06% reach level 6. The minimum perceived safety level is equal to 2 for e-scooter riding with a relatively small percentage of 0.40%. The interventions included in Scenario 1 create a road network of 27.74 km for which it becomes safer to use an e-scooter. Simultaneously, there are no obvious changes in the perceived safety of car driving. For walking, more than the 50% of the links reach at level 6 or higher in Scenario 1. Therefore, the perceived safety of all the examined first/last mile was reinforced from Scenario 0 to Scenario 1.

The next step refers to the determination of the shortest route using the Dijkstra algorithm. E-scooter and walking as transport modes can be used in all links, while the access of cars is prohibited in some links based on traffic regulations, which are currently still valid. For walking, all links are two-way, while directions are fully respected by e-scooter riders and car drivers. All paths refer to trips from node 9000 to node 4000. The main innovation of this process is that a threshold which refers to the minimum-acceptable perceived safety is used to create the input road network (i.e., transport supply). Six thresholds are used in this analysis, i.e., 1, 2, 3, 4, 5, and 6. Table 1 shows the results of this process.

Considering Scenario 0, a path containing links of level 5 or more exists only for car driving; this path is not the shortest. The length of the shortest path is equal to 5241.76 m. This path contains links to walking with a safety level 4 or more. Yet, the algorithm fails to define safe paths for e-scooter riding. As it can be observed, there is no combination of links at level 4 or higher that can be followed so that an e-scooter rider can reach his/her destination. This reality partly changes by implementing Scenario 1. A road network with links at level 3 can be developed; this network is used by e-scooters to travel, increasing the total trip distance by only 499.30 m. Moreover, a safe route (psafe ≥ 6) for walking from node 9000 to node 4000 is created in Scenario 1, upgrading the overall walkability of the road network.

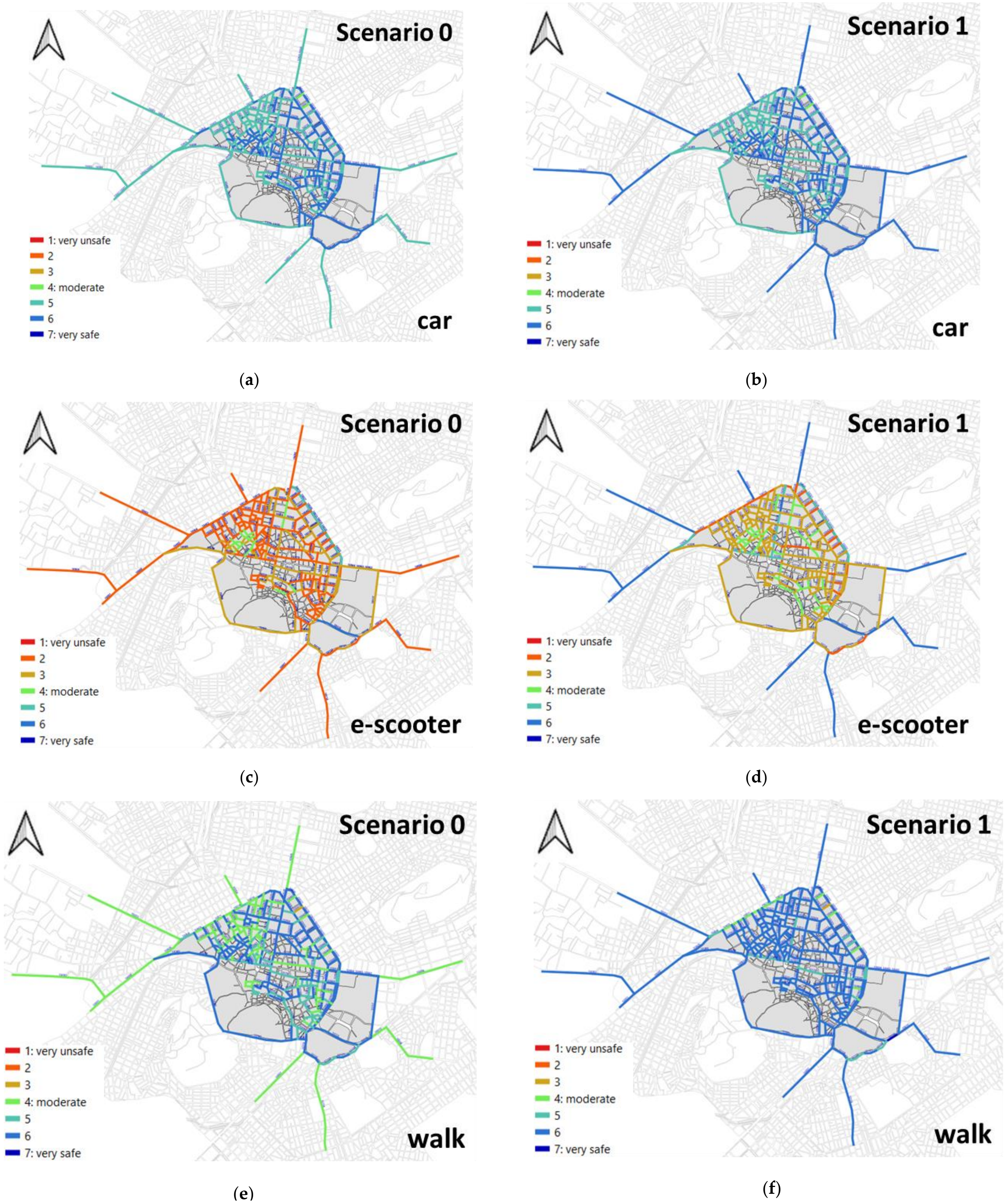



**Figure 5.** Evaluation of perceived safety: (**a**) car, Scenario 0; (**b**) car, Scenario 1; (**c**) e-scooter, Scenario 0; (**d**) e-scooter, Scenario 1; (**e**) walk, Scenario 0; and (**f**) walk, Scenario 1.

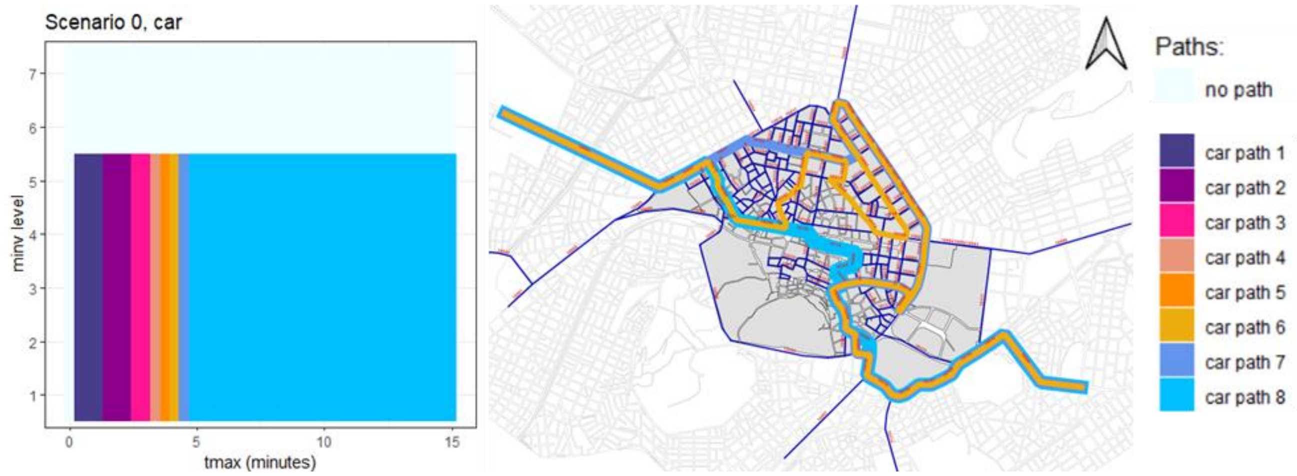
**Table 1.** Distance (m) of the shortest paths per mode per scenario.

| | **Mode** | **Minimum Perceived Safety Level (x ≥ minv)** | | | | | |
|---|---|---|---|---|---|---|---|
| | | **1** | **2** | **3** | **4** | **5** | **6** |
| **Scenario 0** | car | 5476.46 | 5476.46 | 5476.46 | 5476.46 | 5476.46 | no path |
| | e-scooter | 5241.76 | 5241.76 | no path | no path | no path | no path |
| | walk | 5241.76 | 5241.76 | 5241.76 | 5241.76 | no path | no path |
| **Scenario 1** | car | 5476.46 | 5476.46 | 5476.46 | 5476.46 | 5476.46 | no path |
| | e-scooter | 5241.76 | 5241.76 | 5741.05 | no path | no path | no path |
| | walk | 5241.76 | 5241.76 | 5241.76 | 5241.76 | 5241.76 | 5741.05 |

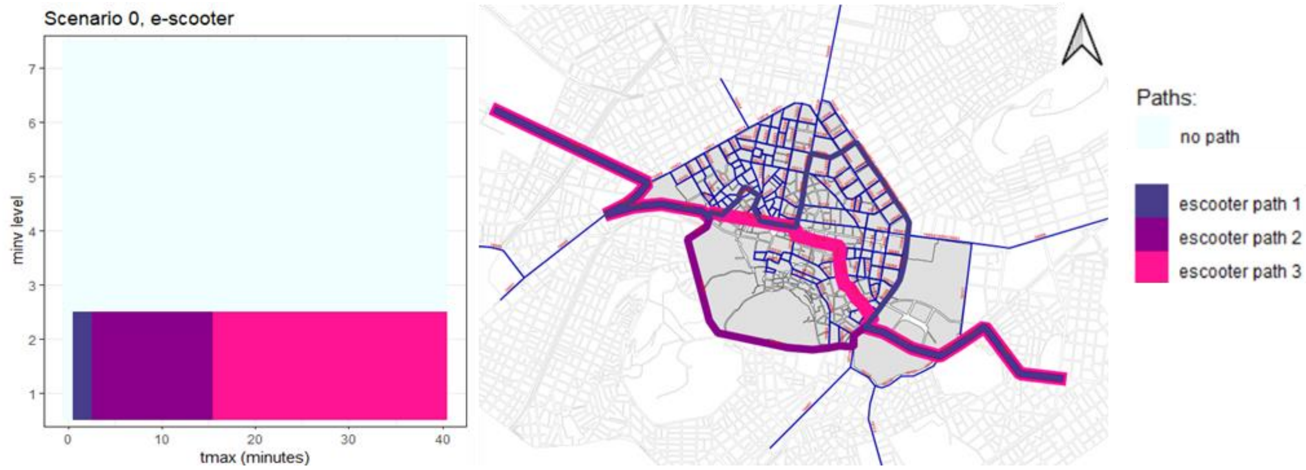
As has been mentioned, the magnitude of perceived safety is influenced by the maximum distance ($d_{max}$), after which safety evaluation really matters. To investigate the impact of this parameter, a simulation is performed importing various values of $d_{max}$, ranging from 250 to 10,000 m. The outputs of this simulation process per mode and per scenario are given in tables in Appendix A. Figures 6 and 7 present the best three alternative paths per examined transport mode of Scenarios 0 and 1, respectively. The best alternative paths combine only links with the maximum possible perceived safety level, while their lengths do not differ much from the shortest path. Additionally, the graphs of the next figures visualize the impact of each utility parameter. The minimum-accepted unsafe distance is divided by the speed of each transport mode to allow meaningful comparisons among modes. The minimum-accepted perceived safety level is integrated in this analysis.

Starting with Scenario 0, for e-scooters, detouring is required for those who perceive a 500 m long link as unsafe; this "unsafety" perception leads to an addition of 1642 m. Riders who remain unaffected by network discontinuities of more than 4000 m do not modify their paths. As can be seen in Figure 6b, for e-scooters users, the model exports three alternative paths with few overlaps compared to other modes. In car driving, this change also happens for a minimum-acceptable unsafe distance lower than 3.0 km. Links with this length can be covered in 4.5 min at a constant car speed of 40 km/h. This means that car drivers who are not willing to drive for 4.5 min in an unsafe link will detour. Tellingly, this parameter value is unrealistically low; that is why the model exports unrealistic paths with much detouring, resulting in an additional distance of more than 2.2 km (see car path 5 in Figure 6a). When walking, travelers tend to differentiate their routes from the shortest path, when the $d_{min}$ is equal to or lower than 2.25 km. In other words, an "unsafety" feeling for more than 27 min is enough to modify pedestrians' routes. In Scenario 0, the exported walking paths are almost similar, as they differ only by 130 m. The model projects that pedestrians will follow the pedestrianized street of Dion. Aeropagitou in order to safely reach their destination (see Figure 6c); this is a fairly realistic result.

Continuing to Scenario 1, it is promising that the modifications in Scenario 1 lead to the generation of two alternative paths of 5767.51 and 5746.58 m to use an e-scooter (see Figure 7b). These lengths are really close to the shortest path, while the perceived safety of the links included in these two paths is level 3 or higher. As it can be observed, the model projects that e-scooter users will use the bike lanes established on the streets of Vas. Olgas, Athinas, and Ermou when travelling through the city center of Athens. Shared-space roads support the access to these lanes. Additionally, by importing Scenario 1, the model can define a path with high perceived safety (i.e., level 6 or higher) for pedestrians. Simultaneously, as it can be seen in Figure 7c, the next alternative paths are unrealistically long. This is related to the fact that the number of safe links to walk increased from Scenario 0 to Scenario 1. There are no significant discontinuities in the road networks. Thus, the model combines as many as possible safe links in order to increase the overall utility of the walk trip. This leads to an additional distance of approximately 3.25 km compared to the best alternative path along the street of Dion. Aeropagitou. In regard to car driving, new paths are formulated by implementing Scenario 1. Car driving paths seem to decline from the shortest route when applying a distance threshold of 4.0 km or lower. The model formulates paths for car drivers in order to avoid shared space links, while combining links with cycle lanes and wide sidewalks that ensure higher levels of perceived safety (see car path 15 in Figure 7a).



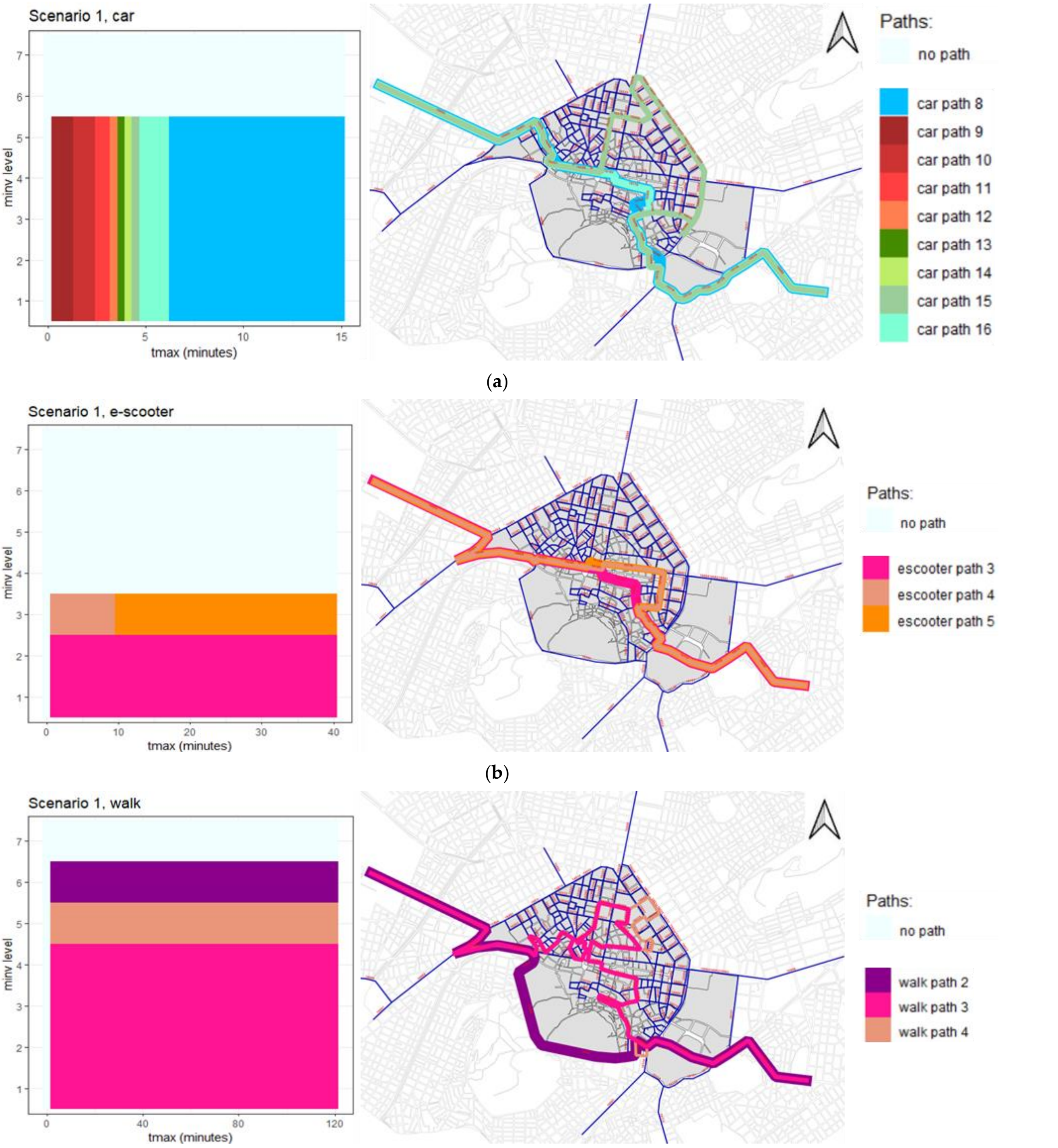

(a)




(b)


(c)

**Figure 6.** Raster plots/maps of best alternative paths as function of the minimum-accepted perceived safety level and maximum-accepted unsafe travel time for Scenario 0: (**a**) car, (**b**) e-scooter, and (**c**) walking.




(**a**) (**b**) (**c**)

**Figure 7.** Raster plots/maps of best alternative paths as function of the minimum-accepted perceived safety level and maximum-accepted unsafe travel time for Scenario 1: (**a**) car, (**b**) e-scooter, and (**c**) walk.

## 5. Discussion

Micro-mobility modes, such as e-scooters, aspired to solve the so-called first/last mile problem [2]. The promises that were made are based on the idea that e-scooter sharing services can be integrated into any transport system in the world without the need for specialized infrastructure [74]. This hypothesis is valid only theoretically, as recent studies have revealed safety issues that emerge due to the integration of e-scooters in cities with different road environments [19,20]. This study assumed that the flexibility of the e-scooter compared to traditional first/last mile modes (e.g., car or walking) is limited in practice by the users' safety perceptions. The unsafety of using a specific transport mode has a cost that can be expressed in monetary values (e.g., EUR) or additional trip distance, as recent studies have highlighted [37–39]. The modeling approach that is proposed in this study is based on two parametric models, namely the perceived safety model and first/last mile routing model. The meaning of each parameter is further discussed in this section.

The absence of specialized Infrastructure for active modes in Athens, Greece, seems to create insuperable safety problems when using micro-mobility modes [72,75]. The perceived safety evaluations in the present situation scenario can provide a sufficient explanation as to why the usages of e-scooters and bicycles is lower than 2% in Athens today [53]. According to the applied perceived safety models, links with cycle lanes and good pavement conditions are scored with high safety values considering all the examined transport modes. The calibration of these models was based on safety evaluations provided by people who live in this city. These reported safety patterns seem to be in line with the literature findings [13,15,36–39]. Nevertheless, the re-calibration of these models is recommended in each study case to accurately represent citizens' safety perceptions [53]. This means a new set of beta parameters and kappa thresholds per examined transport mode. Furthermore, this framework can be extended by taking the subjectivity of perceived safety into account. This can be performed through the integration of random beta variables in the ordinal models, which can explain the heterogeneity in safety perceptions among individuals, and a Monte Carlo simulation can provide an approximation of the overall supply of the road network.

The developed perceived safety models can be utilized as a decision-making tool by transport planners. This tool can uncover spatial discontinuities [13] that appear in the road network and assess the effectiveness of sustainable mobility measures, such as cycling network [69], traffic calming areas [76], superblocks [77], and shared space [27,28]. These measures aspire to balance perceived safety levels and prioritize active modes and micro-mobility, leading to a fairer allocation of urban space [78]. Indeed, by implementing Scenario 1, which proposes the construction of cycle lanes in arterials and shared spaces in inner-road networks, the perceived safety of e-scooter riding and walking was generally improved. Additionally, car drivers' perceived safety was not reduced. This is proven by the distributions of perceived safety levels, which can be interpreted as a significant indication of the proposed measures' effectiveness.

The impact of perceived safety factor on route choices differs among urban transport modes. The car is the dominant urban transport mode [79,80], and this dominance can be described as having relatively high perceived safety levels, which appear in all links of the test scenarios developed in the city center of Athens, Greece. Therefore, car drivers have no reason to detour when covering the first/last mile in comparison to e-scooter riders, who face significant safety discontinuities. Hence, perceived safety as a factor matters more for e-scooter users. It represents a heterogenous road environment which challenges the use of micro-mobility modes. This is the reason why the developed model proved to be useful in the description of e-scooter routing behavior. Previous studies have confirmed the existence of noticeable deviations between real trajectories and model outputs, when the road environment is not considered in the utility function of micro-mobility modes [29,36,39,42]. The developed model solved this issue by minimizing unnecessary detours, while defining safe alternative path with few overlaps. Simultaneously, for walking, the model seems to work well in defining pedestrian-safe paths when importing the present situation scenario. Yet, by balancing perceived safety levels and eliminating unsafe walking discontinuities in Scenario 1, the model fails to define alternative pedestrian paths that are attractive and realistic. Hence, in a homogenous road environment, in terms of safety perceptions, perceived safety is not yet a routing factor.

The utility function has two additional parameters that must be set per mode before running the perceived safety choice model. To define their impact on the resulting routes, a simulation using different parameter settings was performed. The minimum-accepted perceived safety level (minv) limits the number of available links and consequently determines the existence or not of a path to connect two nodes using one transport mode. Therefore, it is a factor related to the accessibility of the road network. By integrating high minv values, the chance of finding one or more alternative paths is decreased. Yet, the formulation of paths by the proposed model is mainly affected by the maximum-accepted unsafe distance ($d_{max}$), especially when the road network contains significant discontinuities in terms of perceived safety. In reality, discontinuities in active modes network increase the number of conflicts [65], affect comfort, and create confusion [17]. The $d_{max}$ parameter determines the magnitude of perceived safety in the utility of one transport mode, describing the unwillingness of certain road users to experience unsafety for an increased number of meters or minutes. The higher the $d_{max}$ parameter is the more detours from the shortest path occur.

Overall, the developed utility function can be integrated into other simulators or trip assignment/routing models following more stochastic approaches. This study used an all-or-nothing routing algorithm (i.e., Dijkstra) to test various settings of parameters in a real road networks. This is a major limitation of this study. Another shortcoming is that the interactions among road users were not considered when estimating perceived safety. In mixed traffic road environments, these can cause long travel delays, increasing the disutility of a single transport mode [81]. These additional and complicated dynamics cannot perfectly be described using static routing algorithms. Agent-based models can simulate this complex reality [28]. Another limitation is the consideration of a fixed travel speed of 40 km/h for car driving. Speed limit and drivers' compliance rate per link can be additional parameters of the developed routing model that affect link utility and therefore the exported travel paths. Experience and other socio-demographic factors can be additional variables of perceived safety and routing behavior; these are not considered in this study. Nevertheless, their inclusion in the modeling framework can be achieved by utilizing a proper parameter setting of the utility functions that may differ by individual.

## 6. Conclusions

This study presented a novel modeling approach to solve the first/last mile routing problem, considering micro-mobility modes. As e-scooters are flexible modes that can move in different road environments, the developed model evaluates the perceived safety of these environments based on a 7-point Likert scale. Perceived safety differs not only by urban road but by transport mode as well. At the same time, this novel approach hypothesizes that subjective unsafety has a cost regarding the utility of each mode, which can be translated into additional distance, thus allowing the road user to avoid unsafe paths. This study applied Dijkstra, an all-or-nothing deterministic algorithm, to define the best alternative paths by transport mode in an experimental road network developed in the city center of Athens, Greece.

Regarding the main findings, it is clear that e-scooter is the least safe option to move through the selected urban area compared to classic first/last mile modes, namely car and walking. The existence of safety discontinuities forces e-scooter riders to detour, increasing the travel distance from origin to destination. Therefore, the flexibility of this micro-mobility mode seems to be limited in reality by the low-perceived safety level, which arises as a result of the lack of specialized infrastructure for micro-mobility modes. As the results showed, the usefulness of this novel modeling approach is related to the existence of a heterogenous road environment in terms of safety perceptions that challenge the use of a single transport mode. Moreover, classical trip assignment algorithms should be preferred to model first/last mile trips. Model outputs also highlight that by implementing measures that prioritize active modes and support the vision of sustainable mobility (i.e., cycle lanes and shared spaces), perceived safety is balanced among transport modes. As a result, the paths of e-scooter riders differentiate from those of pedestrians, leading to less detouring. Yet, this depends on the two main parameters of the utility function that should be calibrated, namely the minimum-acceptable perceived safety level and the minimum-acceptable unsafe distance. The model tests proved that the first parameter determines the chance that the model will find at least one safe path, while the second one is related to the impact of unsafe (small) discontinuities existing in the road network regarding the formulation of the best alternative path.

The developed model contributes to the scientific knowledge of the development of macroscopic or mesoscopic simulation tools to integrate micro-mobility through the analysis and modeling of transport operations and further assess its impact on the sustainability of the transport system. It develops a decision-making tool that is based on a universal approach, in which the utility of a first/last mile mode to travel in a specific road environment is influenced by three important parameters, i.e., time, cost, and safety. This novel modeling approach can be integrated into various trip assignment models and simulators.

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**Data Availability Statement:** The model output data that are analyzed in this study can be found here: https://github.com/lotentua/Perceived_safety_choices/tree/main/scenario_athens/output_csv (accessed on 7 September 2022).

**Conflicts of Interest:** The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

## Appendix A

**Table A1.** Car path distances as function of the minimum-accepted perceived safety level and minimum-accepted unsafe distance/travel time.

| dmax (km) | tmax (h) | $x \geq$ minv | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Scenario 0 | | | | | | | Scenario 1 | | | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 0.25 | 0.01 | 10.88 | 10.88 | 10.88 | 10.88 | 10.88 | - | - | 8.55 | 8.55 | 8.55 | 8.55 | 8.55 | - | - |
| 0.50 | 0.01 | 10.88 | 10.88 | 10.88 | 10.88 | 10.88 | - | - | 8.55 | 8.55 | 8.55 | 8.55 | 8.55 | - | - |
| 0.75 | 0.02 | 10.88 | 10.88 | 10.88 | 10.88 | 10.88 | - | - | 8.55 | 8.55 | 8.55 | 8.55 | 8.55 | - | - |
| 1.00 | 0.03 | 10.77 | 10.77 | 10.77 | 10.77 | 10.77 | - | - | 8.45 | 8.45 | 8.45 | 8.45 | 8.45 | - | - |
| 1.25 | 0.03 | 10.77 | 10.77 | 10.77 | 10.77 | 10.77 | - | - | 8.45 | 8.45 | 8.45 | 8.45 | 8.45 | - | - |
| 1.50 | 0.04 | 10.77 | 10.77 | 10.77 | 10.77 | 10.77 | - | - | 8.45 | 8.45 | 8.45 | 8.45 | 8.45 | - | - |
| 1.75 | 0.04 | 10.69 | 10.69 | 10.69 | 10.69 | 10.69 | - | - | 6.19 | 6.19 | 6.19 | 6.19 | 6.19 | - | - |
| 2.00 | 0.05 | 10.69 | 10.69 | 10.69 | 10.69 | 10.69 | - | - | 6.19 | 6.19 | 6.19 | 6.19 | 6.19 | - | - |
| 2.25 | 0.06 | 10.90 | 10.90 | 10.90 | 10.90 | 10.90 | - | - | 10.96 | 10.96 | 10.96 | 10.96 | 10.96 | - | - |
| 2.50 | 0.06 | 10.45 | 10.45 | 10.45 | 10.45 | 10.45 | - | - | 10.51 | 10.51 | 10.51 | 10.51 | 10.51 | - | - |
| 2.75 | 0.07 | 9.81 | 9.81 | 9.81 | 9.81 | 9.81 | - | - | 9.88 | 9.88 | 9.88 | 9.88 | 9.88 | - | - |
| 3.00 | 0.08 | 7.41 | 7.41 | 7.41 | 7.41 | 7.41 | - | - | 8.20 | 8.20 | 8.20 | 8.20 | 8.20 | - | - |

**Table A1.** *Cont.*

| dmax (km) | tmax (h) | x ≥ minv | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Scenario 0 | | | | | | | Scenario 1 | | | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3.25 | 0.08 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | - | - |
| 3.50 | 0.09 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | - | - |
| 3.75 | 0.09 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | - | - |
| 4.00 | 0.10 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.56 | 5.56 | 5.56 | 5.56 | 5.56 | - | - |
| 4.25 | 0.11 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 4.50 | 0.11 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 4.75 | 0.12 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 5.00 | 0.13 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 5.25 | 0.13 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 5.50 | 0.14 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 5.75 | 0.14 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 6.00 | 0.15 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 6.25 | 0.16 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 6.50 | 0.16 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 6.75 | 0.17 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 7.00 | 0.18 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 7.25 | 0.18 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 7.50 | 0.19 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 7.75 | 0.19 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 8.00 | 0.20 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 8.25 | 0.21 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 8.50 | 0.21 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 8.75 | 0.22 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 9.00 | 0.23 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 9.25 | 0.23 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 9.50 | 0.24 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 9.75 | 0.24 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |
| 10.00 | 0.25 | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - | 5.48 | 5.48 | 5.48 | 5.48 | 5.48 | - | - |

**Table A2.** E-scooter path distances as function of the minimum-accepted perceived safety level and minimum-accepted unsafe distance/travel time.

| dmax (km) | tmax (h) | x ≥ minv | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Scenario 0 | | | | | | | Scenario 1 | | | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 0.25 | 0.02 | 6.88 | 6.88 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 0.50 | 0.03 | 6.88 | 6.88 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 0.75 | 0.05 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 1.00 | 0.07 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 1.25 | 0.08 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 1.50 | 0.10 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 1.75 | 0.12 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 2.00 | 0.13 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 2.25 | 0.15 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.77 | - | - | - | - |
| 2.50 | 0.17 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 2.75 | 0.18 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 3.00 | 0.20 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 3.25 | 0.22 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |

**Table A2.** *Cont.*

| dmax (km) | tmax (h) | x ≥ minv | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Scenario 0 | | | | | | | Scenario 1 | | | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 3.50 | 0.23 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 3.75 | 0.25 | 5.74 | 5.74 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 4.00 | 0.27 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 4.25 | 0.28 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 4.50 | 0.30 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 4.75 | 0.32 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 5.00 | 0.33 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 5.25 | 0.35 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 5.50 | 0.37 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 5.75 | 0.38 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 6.00 | 0.40 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 6.25 | 0.42 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 6.50 | 0.43 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 6.75 | 0.45 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 7.00 | 0.47 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 7.25 | 0.48 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 7.50 | 0.50 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 7.75 | 0.52 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 8.00 | 0.53 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 8.25 | 0.55 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 8.50 | 0.57 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 8.75 | 0.58 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 9.00 | 0.60 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 9.25 | 0.62 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 9.50 | 0.63 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 9.75 | 0.65 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |
| 10.00 | 0.67 | 5.24 | 5.24 | - | - | - | - | - | 5.24 | 5.24 | 5.75 | - | - | - | - |

**Table A3.** Walk path distances as function of the minimum-accepted perceived safety level and minimum-accepted unsafe distance/travel time.

| dmax (km) | tmax (h) | x ≥ minv | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Scenario 0 | | | | | | | Scenario 1 | | | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 0.25 | 0.05 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 0.50 | 0.10 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 0.75 | 0.15 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 1.00 | 0.20 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 1.25 | 0.25 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 1.50 | 0.30 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 1.75 | 0.35 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 2.00 | 0.40 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 2.25 | 0.45 | 5.74 | 5.74 | 5.74 | 5.74 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 2.50 | 0.50 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 2.75 | 0.55 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 3.00 | 0.60 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 3.25 | 0.65 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 3.50 | 0.70 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 3.75 | 0.75 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |

**Table A3.** *Cont.*

| dmax (km) | tmax (h) | $x \geq$ minv | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | Scenario 0 | | | | | | | Scenario 1 | | | | | | |
| | | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
| 4.00 | 0.80 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 4.25 | 0.85 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 4.50 | 0.90 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 4.75 | 0.95 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 5.00 | 1.00 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 5.25 | 1.05 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 5.50 | 1.10 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 5.75 | 1.15 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 6.00 | 1.20 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 6.25 | 1.25 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 6.50 | 1.30 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 6.75 | 1.35 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 7.00 | 1.40 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 7.25 | 1.45 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 7.50 | 1.50 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 7.75 | 1.55 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 8.00 | 1.60 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 8.25 | 1.65 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 8.50 | 1.70 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 8.75 | 1.75 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 9.00 | 1.80 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 9.25 | 1.85 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 9.50 | 1.90 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 9.75 | 1.95 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |
| 10.00 | 2.00 | 5.87 | 5.87 | 5.87 | 5.87 | - | - | - | 9.13 | 9.13 | 9.13 | 9.13 | 8.56 | 5.87 | - |

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