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Exploring the effect of perceived safety in first/last mile mode choices

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Abstract

Micro-mobility transport modes like e-bikes and e-scooters promise higher flexibility when covering the first/last mile trip from/to the public transport stop/station to the destination point and vice-versa. However, safety concerns about riding a micro vehicle in mixed traffic limit the flexibility of shared mobility modes and make conventional ones still more attractive, e.g., private car and walking. This study investigates the effect of perceived safety in first/last mile mode choice by conducting an image-based double stated preference experiment targeted at potential micro-mobility users and developing ordinal and mixed logistic regression models. The Value-of-Safety (VoS) is introduced. It refers to the additional distance a user is willing to exchange to avoid an unsafe path. Main findings show that shared space can be a middle-ground solution, as it reports lower heterogeneity among individuals in terms of safety perceptions. The intensive use of e-scooters in mixed-traffic decreases the perceived safety of pedestrians, while e-bikers are threatened by the existence of heavy motorized traffic. Low mean VoS is also reported for e-scooters, demonstrating the unwillingness of potential micro-mobility service users to either detour or use this micro vehicle. The mean VoS of the e-bike is estimated as almost equal to that of the private car. It could be, hence, concluded that perceived safety can systematically explain the unobserved disutility of e-bikes.

Keywords Perceived safety, first/last mile transport · Choice modeling · Travel behavior · Road environment

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Introduction

Micro-mobility aspires to become an integral part of urban transport systems worldwide (Oeschger et al. 2020). Indeed, micro-mobility modes can efficiently facilitate first/last mile trips and enhance multimodality by providing quick access to dense city centers and public transport terminals (OECD/ITF 2020; Yanocha and Allan 2019). E-bikes and e-scooters, two of the most popular micro-mobility modes, have been worldwide introduced as part of innovative shared mobility services, offering a convenient travel option for up to 5 km trips (He et al. 2019; Ling et al. 2017; Liu and Suzuki 2019). Nevertheless, recent studies have argued that the use of micro-mobility modes is not without safety concerns (Aman et al. 2021; Branion-Calles et al. 2019; Sanders et al. 2020a; Sorkou et al. 2022). As Tuncer et al. (2020) observed, these modes tend to follow a dual behavior (from vehicle to pedestrian and vice versa), which can reduce travel time in congested road environments; yet it creates complicated traffic interactions. Such interactions are perceived as unsafe and therefore limit the attractiveness of micro-mobility modes. Therefore, flexibility, which stands out as a notable promise of micro-mobility modes (Badia and Jenelius 2023; Sanders et al. 2020a), is simultaneously their biggest drawback. Previous studies have shown that young well-educated people tend to adopt these services, but that wider adoption beyond this niche user category remains sluggish and below expectations (Eccarius and Lu 2020; Hosseinzadeh et al. 2021; Merlin et al. 2021; Nikiforiadis et al. 2021).

Previous studies have shown that safety concerns are a primary deterrent to bicycle usage, especially in cites without dense cycling networks (Branion-Calles et al. 2019; Heinen et al. 2010; Livingston et al. 2018; Willis et al. 2015). The introduction of exclusive or semi-exclusive cycling infrastructure is considered a safer practice compared to promoting cycling in mixed traffic (Chataway et al. 2014; Manton et al. 2016), while high motorized traffic volumes and speeds negatively affect the perceived safety of cyclists (Buehler and Dill 2016). But while segregation seems to be the obvious choice in many contexts, in dense urban areas it is often difficult to implement, as planners must deal with public space constraints (Nikitas et al. 2021; Tzamourani et al. 2022). Space sharing, as opposed to segregating, is often the preferred approach in such environments due to advantages relating to reinforcing the "place" function of streets (Diemer et al. 2018; SWOV 2013; Tsigdinos and Vlastos 2020). To this end, a previous study by Tsigdinos et al. (2022) explored the transformation of the future urban road and underlined an important dilemma faced by researchers and planners in the future: *"to share or to segregate?"*. Multimodal corridors support segregation by creating facilities and corridors for all transport modes in an equitable manner (Tsigdinos et al. 2020). On the contrary, shared space asks road users to co-exist in the same road environment by lowering traffic speeds and increasing traffic interactions (Batista et al. 2022; Hamilton-Baillie 2008; Kaparias et al. 2011). It is based on the risk homeostasis theory, where humans shift the balance of risk according to their environment (Hammond and Musselwhite 2013). In other words, the interactions among road users can form the way based on which micro-mobility modes can co-exist solving automatically the space allocation problem. In this context, the perceived safety of road users seems to be a catalytic factor that may determine whether the coexistence of classic and new urban transport modes can be feasible (Akgün-Tanbay et al. 2022; Tzouras et al. 2021).

The study by Gill et al. (2022) mentions that *"perceived safety refers to an individual's level of concern for being in a crash or injured"*. Perceived safety differs from objective safety which refers to a low risk of a crash or injury and is estimated based on "real" conflicts or accidents collected from the field (Gkekas et al. 2020; Tzouras et al. 2020). As a subjective notion, perceived safety varies not only per transport mode but per individual. In micro-mobility modes, various studies directly connect perceived safety with comfort (Chataway et al. 2014; Dill and McNeil 2013). A "safe" e-bike or e-scooter ride is a "comfortable" ride and vice versa (Bhagat-Conway et al. 2022). Last, the road environment can be considered as a significant determinant of comfort and therefore perceived safety. Therefore, it is hypothesized that perceived safety influences route or mode choices in heterogenous urban road environments, as it affects the utility of specific modes.

In this context, this paper attempts to model the impact of perceived safety of potential micro-mobility users, with respect to first/last mile mode choices, in dense urban areas. General safety perceptions are examined across four first/last mile transport modes: private car, e-bike, e-scooter, and walking. The objective is to identify how the distinct characteristics of each vehicle contribute to discernible differences in safety perceptions. Additionally, perceived safety is explored considering various road environments and traffic conditions in order to provide some meaningful answers to the dilemma of sharing or segregating. Significant demographic factors that influence the attractiveness and consequently the demand for first/last mile transport services are identified as well. It should be noted that a potential micro-mobility user targeted in this study is defined as an active, well-educated individual, preferably below 40 years old, who is familiar with technological advancements and does not own an e-scooter (Sorkou et al. 2022). The study examines the tastes of such an inexperienced micro-mobility user, to uncover the safety conditions under which the integration of shared micro-mobility modes can change mobility patterns and travel behavior in cities.

The paper is structured as follows: An extensive literature review of recent studies (Sect. 2) is conducted, before developing an image-based, double stated preference experiment in Sect. 3. Next, collected data are analyzed by developing ordinal logistic regression models with random parameters for analyzing safety ratings and estimating mixed logit models for describing mode choices (Sect. 4). Model outputs are discussed compared to the literature in Sect. 5 and study limitations are presented before deriving valid conclusions in Sect. 6.

Literature review

Safety concerns are divided into three broad categories, i.e., (a) personal safety which refers to freedom from threats of crime, harassment, etc., (b) traffic safety which is about freedom from threats of injury due to a collision and (c) property safety that refers to freedom of threats of theft (Bhagat-Conway et al. 2022). This study particularly deals with perceived traffic safety. Table 1 summarizes major relevant studies on that topic. Previous studies mainly conducted stated preferences experiments to quantify this subjective factor and predict its impact on driving/travel behavior. The study by Park and Park (2021) indicated that the car-exterior context (road conditions, weather, etc.) affects the perceived safety and consequently the enjoyment of elderly drivers, in particular.

Continuing with micro-mobility modes, Calvey et al. (2015) analyzed cyclists' perceptions of satisfaction and comfort to propose a new inspection method. The results showed that satisfaction is linked both with comfort and safety. Non-asphalt pavements seem to

Table 1 Summary of previous studies' findings about perceived safety

Study	Road user type	Data collection method	Noticed factors/Findings
Calvey et al. (2015)	cyclists	- questionnaire survey with Likert Scale	- non-asphalt pavements increase vibrations resulting in reduced comfort, safety and therefore satisfaction.
Bai et al. (2017a)	cyclists	- image-based rating experiment	- comfort perceptions are proportional to the width of the mid-block cycle lane; - females and middle-aged or older users are more concerned.
Branion-Calles et al. (2019)	cyclists	- three repeat cross-sectional surveys	- odds of perceiving bicycling as safe are increased in urban areas with at least 1 km available bicycle infrastructure.
Gkekas et al. (2020)	cyclists pedestrians	- intercept survey	- cyclists are less concerned about intermodal conflicts compared to pedestrians; - cyclists tend to avoid pedestrian-dominated areas and motorized traffic.
Hidayati et al. (2020)	pedestrians	- on - street interviews - survey responses	- perceived safety of pedestrians is influenced by the volume of motorcycles who follow a risk-taking behavior.
Aceves-González et al. (2020)	pedestrians	- physical audit - on-street questionnaire	- curbs and surface quality, existence of pedestrian crossings, obstacles on the sidewalk and traffic lights influence perceived safety.
Park and Park (2021)	car drivers	- face-to-face survey	- weather, road conditions, etc. affect perceived safety of elderly drivers especially.
Kaparias et al. (2012)	car drivers pedestrians	- two web-based stated preferences experiments	- car drivers' perceptions are influenced by the presence/absence of children and pedestrian density; - vehicle traffic, provision of safe zones, lighting level, age and gender determine perceived safety of pedestrians.
Akgün-Tanbay et al. (2022)	cyclists e-scooter riders pedestrians	- face-to-face survey	-experienced users seem to not find shared space chaotic; - females underrate perceived safety of walking and cycling.
Useche et al. (2021)	cyclists	- Cycling Behavior Questionnaire	- experienced cyclists seem to be more aware of traffic regulations and have a higher risk perception.
Kopplin et al. (2021)	e-scooter riders	- questionnaire survey with Likert Scale	- the intention to use an e-scooter as a fun object is limited by safety concerns expressed mainly by people who do not own one.
Gill et al. (2022)	pedestrians	- online survey with videos	- perceived safety of pedestrians relates to vehicle acceleration/deceleration rate, while perceived comfort is influenced by vehicles speed; - more frequent walking on city streets results to increased perceived safety.
Fitch et al. (2022a)	cyclists	- on-line video experiment	- in a high speed, high volume arterials, the construction of a well-designed on-road bike facility may not be enough to raise comfort ratings.
Bosen et al. (2023)	cyclists	- problem-centred interviews	- high perceived safety of experienced cyclists is not due to the absence of risks, but depends on perceived efficacy of individual mitigation strategies in unexpected events.
Olsson et al. (2023)	cyclists	- quasi-experimental survey in photo-manipulated bicycle streets	- all street designs are perceived as more unsafe if there are many cars - cyclists feel safer in roads with clear horizontal signs compared to vertical signs - a red-coloured cycle lane performs best

Table 1 (continued)

Study	Road user type	Data collection method	Noticed factors/Findings
Cubells et al. (2023)	e-scooter riders	- GPS tracked trips	- because of unsafety perceptions, a minority of e-scooter riders use the shortest path, - e-scooter riders do not detour in order to follow bicycle sharrows or pedestrianized zones.
Nikiforiadis et al. (2023)	cyclists, pedestrians	- data from 5 shared infrastructures	- pavement quality is essential for all road users - cyclists' behaviour impact the perceived quality and safety of pedestrians - perceived quality is affected by the age, but by the gender.
Martínez-Díaz & Arroyo (2023)	cyclists	- expert interviews	- safety perception depends on trip purpose: daily users vs. cycling for sport - the continuity of infrastructure changes safety perceptions - traffic calming has positive yet not decisive impact
Hernandez and Zegras (2023)	cyclists	- randomized control trial framework with photo simulations of BRT design alternatives	- a painted bus lane and the addition of cycle lane enhances safety perceptions of cyclists - the incorporation of green spaces instead of car parking increases perceived safety and well-being factors

increase vibrations of cyclists resulting in reduced comfort, safety, and therefore satisfaction. Similarly, Bai et al. (2017a) developed an ordered probit regression model to examine the perceived comfort of e-bike and e-scooter riders in various urban environments. The model outputs show that e-scooters are perceived as less comfortable compared to e-bikes. The comfort perceptions of cyclists are proportional to the width of the mid-block cycle lane. Next, the study of Branion-Calles et al. (2019) showed that the odds of perceiving bicycling as safe are increased in urban areas with available bicycle infrastructure with at least 1 km network distance. In the examined cities, cyclists are mostly young males belonging to lower-income groups, while the ownership of a bicycle is a necessary pre-condition. Useche et al. (2021) compared risk perceptions between micro-mobility riders and non-riders; they found that experienced cyclists seem to be more aware of traffic regulations and have a higher risk perception. Kopplin et al. (2021) added that the intention to use an e-scooter as a fun object is seriously limited by safety concerns expressed mainly by people who do not own a micro-mobility vehicle. A more recent study by Fitch et al. (2022) examined the perceived comfort of cyclists by conducting an on-line video experiment. They approached bicyclists' comfort as a parallel variable of perceived safety. The bicycle comfort ratings proved that the presence of bike infrastructure results in higher comfort ratings. Yet, in high-speed, high-volume arterials, the construction of a well-designed on-road bike facility may not be enough to raise the comfort ratings of women and older participants. Last, Bosen et al. (2023) explored utility cycling along a central route in Aachen, Germany, through problem-centered interviews with ten experienced cyclists. The study revealed that continued commitment to urban cycling under challenging conditions is less about the absence of perceived risks and more about trust in the effectiveness of personal strategies to mitigate those perceived risks.

It is questionable if perceived safety and comfort as subjective factors can be used interchangeably in transport models especially when modeling pedestrians' travel behavior. The study of Hidayati et al. (2020) seems to mix these two factors revealing contradicting findings. In Jakarta, Indonesia, perceived safety seems to be influenced by the volume of motorcycles that usually follow reckless or risk-taking behavior. In Kuala Lumpur, Malaysia, pedestrians' safety perceptions and route choices seem to be correlated with the presence of pedestrians and shops in the urban road environment. The study of Gill et al. (2022) argued that pedestrians' safety perceptions differ from comfort perceptions at non-signalized crosswalks. Their results show that the perception of yielding is a strong determinant of safety and comfort perception. The perceived safety of pedestrians seems to be more related to vehicle acceleration/deceleration rates, while perceived comfort is influenced by vehicle speeds. Experienced pedestrians (i.e., people who walk daily to commute) expressed lower perceived comfort levels due to past incidents; yet more frequent walking on city streets results in increased perceived safety. In general, according to the survey results of Aceves-González et al. (2020), the perceived safety of pedestrians is influenced by various factors related to the road environment, e.g., curbs and surface quality, the existence of pedestrian crossings, obstacles on the sidewalk and traffic lights. Indeed, the study of Olsson et al. (2023) underlined the intricate challenge of complex urban road environments that influence specific feelings or experiences, noting that environments feel less safe to cyclists with more cars present. Residents of Gothenburg (where this study was conducted) were accustomed to local cycling conditions and perceived these environments as safer compared to non-residents. According to Cubells et al. (2023), e-scooter riders, tend to avoid the shortest paths, opting instead for routes that offer better safety, accessibility, and aesthetic qualities,. The study also found gender differences in navigation preferences, with women taking shorter detours and a pronounced preference among e-scooter riders for using bicycle lanes.

Mixed traffic environments like shared space have been used as an experimental field to examine the impact of complex traffic interactions on perceived safety and therefore travel/driving behavior. The study by Gkekas et al. (2020) found that cyclists are less concerned about intermodal conflicts compared to pedestrians. Cyclists tend to avoid pedestrian-dominated areas; yet this tendency is balanced by the additional travel time to perform safe detours and their preference to avoid motorized traffic in any case. Furthermore, Kaparias et al. (2012) indicated that car drivers' perceptions are influenced by the presence/absence of children and pedestrian density in shared space. Vehicle traffic, provision of safe zones, lighting level, age, and gender were among the most significant variables that determined the perceived safety of pedestrians. In a follow-up study that focused on the willingness of Powered Two-Wheler (PTW) riders to share the space, it was revealed that the existence of high pedestrian flows and static obstacles leads to a lower willingness of two-wheelers to share the space (Kaparias and Li 2021). A similar approach was followed by the study of Akgün-Tanbay et al. (2022). According to their findings, experienced users seem to not find shared space as chaotic as it was expected, while females underrated the perceived safety of walking and cycling in shared spaces. Nikiforiadis et al. (2023) noted that familiarity with pedestrian coexistence increases cyclists' safety and comfort, suggesting that advanced cycling cultures promote harmonious pedestrian-cyclist relations, bolstered by cyclists' growing confidence and safety perceptions through experience. Yet, the study of Martínez-Díaz and Arroyo (2023) emphasized the need for spatial and temporal planning to enhance safety perceptions in Helsinki, Finland and Barcelona, Spain, advocating for continuous cycling infrastructure along major routes, complemented by traffic calming measures and physical separation from traffic, though these are seen as beneficial yet not critical.

Last, Hernandez and Zegras (2023) explored how various Bus Rapid Transit (BRT) design options affect travelers' subjective well-being. It was revealed that a painted bus lane and the addition of a cycle lane, combined with buffer green zones, enhances safety perceptions of cyclists in arterials.

Still, safety perceptions about using (or not) a particular transport mode to cover the first/last mile in heterogeneous road environments have never been compared and discussed in the literature. This study "measures" this effect, assuming that a considerable proportion of the unobserved disutility of especially micro-mobility modes lies in perceived traffic safety, while it is influenced by road environment attributes. Based on this hypothesis, this work contributes to the literature by proposing a new, "universal" modeling framework that assembles all the previously mentioned puzzle pieces. The framework simultaneously quantifies the perceived safety of various urban road environments and investigates the impact on first/last mile mode choices.

Methodology

For the purposes of this study, data are collected by deploying an image-based double stated preferences experiment. According to Gill et al. (2022), user perceptions can be quantified by collecting either first-person or third-person evaluations. In the first approach, the respondents experience a traffic situation in a real or simulated world before rating their perceptions, while in third-person rating experiments, the respondents inspect a road environment in which they have not taken part before providing a score. In the present case, a third-person, double stated preference experiment is adopted: participants first rate perceived safety per transport mode considering a set of images that present some hypothetical scenarios. Second based on their individual ratings, respondents are asked to choose a transport mode for their first/last mile trip; time and cost are integrated as additional factors.

The transport modes that are included in the experiment are car, e-bike, e-scooter, and walk. It is assumed that the safety perceptions in flat terrains of cyclists do not significantly differ from e-cyclists. E-bikes have already been identified as a promising solution to overcome a very important barrier of first/last mile cycling, i.e., the hilly terrain (He et al. 2019; Ling et al. 2017; Liu and Suzuki 2019). It should be noted that this experiment does not examine the impact of a hilly terrain on perceived safety and travel behavior of cyclists. This assumption is reasonable for e-bikes, where users can maintain their cycling speed by utilizing the power of electric motor. Still, in conventional bicycles, cyclists may experience increased pressure from surrounding motorized traffic, which typically moves at higher speeds, thus becoming a significant determinant of perceived safety. E-bikes cannot be grouped with e-scooter, as previous studies have reported significant deviations in users' comfort perceptions (Bai et al. 2017a) and routing behavior between these two modes (Useche et al. 2022; Younes and Baiocchi 2022).

Variables selection and definition of variable levels

In this experiment, two dependent variables are investigated. The first one refers to perceived safety, which is assumed to be represented by an ordinal variable since its quantification follows a 7-point Likert scale, where 1 corresponds to "very unsafe, 4 to moderately safe, and 7 to "very safe" perceptions. This 7-point Likert scale is preferred, as it provides enough options that are closer to the original opinions of the respondents and reduces the role of ambiguity in the responses compared to the 5-point scale (Joshi et al. 2015). The second dependent variable refers to the first/last mile mode choice. Mode choice is a nominal variable consisting of the four aforementioned categories: car, e-bike, e-scooter, walk. Perceived safety acts as an explanatory variable of mode choice. In addition, the mode choice nominal variable is next converted to a set of four binary variables, with each of them representing the choice (use) or not of a transport mode, i.e., use or not use the mode m. This conversion is used for estimating the willingness of road users to detour (i.e., add some meters/kilometers in the first/last mile path) if they are to experience a better perceived safety level. A similar approach has been followed by some recent studies that dealt with cycling route choices (Meister et al. 2022; Reggiani et al. 2022).

Regarding the independent variables which are presented in Table 2, this study considers socio-demographic characteristics which may influence safety perceptions and therefore modes choices. These include gender, age, education level, and monthly income are among these variables (Bhagat-Conway et al. 2022). Also, respondents are asked to describe their current travel choices, i.e., frequency of using each mode. Having a driving license, and owning a private car or a micro-mobility mode in the household are integrated into the modeling exercise as additional variables. The experiment investigates the frequency of using private cars and micro-mobility modes for first/last mile trips respondents. Nevertheless, the previously mentioned variables are not introduced in the scenario design process, as they cannot be controlled a priori.

Experimental variables are defined by synthesizing and integrating the findings of previous studies aiming to create a more generalizable framework. Four different infrastructure types are selected; these are four different cross-section designs that can appear in a typical 17.5 m wide urban road in Athens, Greece (see Fig. 1). Type 1 presents an extreme, yet real case, where almost the 88% space is fully allocated to motorized traffic. The width of the sidewalk does not exceed 1.5 m. The traffic lanes width is 5.85 m, while there is a 2.1 m wide parking lane in both sides of the street. Type 2 is a more "walkable" road with wide sidewalks of 2.1 m. Full segregation of traffic flows is achieved in Type 0, where a 3 m wide unidirectional cycle lane is established, and the sidewalk is wider than 2.0 m in both sides. There is also 1.0 m buffer zone between the cycle lane and the space dedicated to motorized traffic. Hence, the parking lane is removed. In essence, it is a multimodal travel corridor, where space has been distributed sufficiently to all modes (Tsigdinos et al. 2020; Tzamourani et al. 2022). On the contrary, type 3 is a shared space design. There is a visual (but not level) segregation of the sidewalk, while the speed limit is decreased from 50 to 30 km/h in this case only. According to Kaparias and Wang (2020), shared space can be considered as an umbrella term that encloses designs and measures which promote the co-existence of road users while avoiding physical separation. The various design proposals for shared space seem to influence pedestrian crossing behavior which disturbs traffic flow (Batista and Friedrich 2022; Tzouras et al. 2023). That is why an additional independent variable related to the existence and the type of "zebra" pedestrian crossings is included in the analysis (signalized and non-signalized). Pavement condition is expected to be a significant variable of perceived safety; its negative impact which seems to be proportional to the frequency of vibrations has been widely discussed in previous studies (Calvey et al. 2015; Kaparias and Li 2021; Ma et al. 2021; Sorkou et al. 2022). Two levels are determined, i.e.,

Table 2 Presentation of independent variables

Independent variable	No. of levels	Variable levels				
		Level 0	Level 1	Level 2	Level 3	Level 4
A. Variables related to socio-demographic characteristics						
Gender	2	male	female			
Age	2	≥ 30 years old	< 30 years old			
Education Level	5	no education	primary	secondary	higher	master or PhD
Monthly Income (per individual)	5	no income	< 750 €/month	750–1500 €/month	1500–2500 €/month	≥ 2500 €/month
B. Variables related to travel behavior (revealed preferences)						
Driving license	2	no	yes			
Car-ownership	4	none	1 car	2 cars	3 or more cars	
Car use frequency	4	almost never	sometimes in a year	sometimes in a month	sometimes in a week	daily
Bicycle (or e-bike)/e-scooter ownership	2	none	1 or more bicycles/e-scooters			
Bicycle (or e-bike)/e-scooter use frequency	5	almost never	sometimes in a year	sometimes in a month	sometimes in a week	daily
C. Variables related to the road environment						
Road infra-structure	4	unidirectional urban road (50 km/h speed limit)	unidirectional urban road (50 km/h speed limit)	unidirectional urban road (50 km/h speed limit)	Shared space (30 km/h speed limit)	
		with cycle lane	no cycle lane	no cycle lane		
		sidewalks ≥ 1.5 m wide	sidewalks < 1.5 m wide	sidewalks ≥ 1.5 m wide		
Pavement condition	2	bad condition	good condition			
Obstacles	2	no obstacles	many obstacles			

Table 2 (continued)

Independent variable	No. of levels	Variable levels				
		Level 0	Level 1	Level 2	Level 3	Level 4
"Zebra" Pedestrian crossings	3	without "zebra" pedes-trian crossings	with "zebra" pedestrian crossings	with "zebra" pedestrian crossing		
		absence of road markings	not controlled by traffic lights	controlled by traffic lights		
D. Variables related to the traffic conditions						
Vehicle density	3		100 veh/km/dir	60 veh/km/dir	20 veh/km/dir	
Bike density	3		90 bikes/km/dir	50 bikes/km/dir	10 bikes/km/dir	
Pedestrians in the road environment	3		25 pedestrians in the road environment (3500 m²)	15 pedestrians in the road environment (3500 m²)	5 pedestrians in the road environment (3500 m²)	
E. Variables related to the trip attributes						
Travel time	3		car: 40 min	car: 20 min	car: 5 min	
			e-bike: 25 min	e-bike: 15 min	e-bike: 5 min	
			e-scooter: 30 min	e-scooter: 20 min	e-scooter: 10 min	
			walk: 45 min	walk: 30 min	walk: 15 min	
Travel cost	3		car: 6.5 euros	car: 5 euros	car: 3.5 euros	
			e-bike: 4.5 euros	e-bike: 3 euros	e-bike: 1.5 euros	
			e-scooter: 3.5 euros	e-scooter: 2 euros	e-scooter: 0.5 euros	
			walk: 0 euros	walk: 0 euros	walk: 0 euros	

bad, and good condition. Pavements with cracks, potholes, or cobblestone pavements are assigned to a bad condition level (Sorkou et al. 2022). Static (or non-moving) objects that exist in the road environment and especially on sidewalks are considered as obstacles. A binary categorical variable is added to describe the existence or not of many obstacles that significantly hinder road users' movements.

Road users and their vehicles are the moving objects of the road environment. To divide them three categories are considered based on their size, speed and vulnerability. Cars, trucks, and buses are considered vehicles, while various micro-mobility modes like e-scooter, e-bikes, or motorcycles are classified as just bikes. Pedestrians are in the last category. Traffic conditions and therefore the complexity of interactions on the urban road can be well described by considering only these three different forces: vehicles (4 wheels) vs. bikes (2 wheels) vs. pedestrians (Polders and Brijs 2018; Schönauer et al. 2012). Further divisions of traffic composition would create complex models of perceived safety which could not be used in practice. Densities instead of flows are utilized as independent variables. Besides, vehicle flows cannot be observed in a set of static images, since the time dimension is missing from these representations of traffic conditions. Vehicle and bike

Fig. 1 Presentation of the four main infrastructure types/scenes (static and moving objects have been added in the scenes)

density factor is measured per km and per direction. Yet, as pedestrian density is usually measured per m^2, a different variable is integrated into this experiment, i.e., the number of pedestrians in the road environment. In this case, the next 200 m comprise the road environment, which directly affects drivers' perception. Indeed, a previous study has showed that the existence of many pedestrians in the next 200 m of a mixed-traffic road directly impacts on the safety perceptions of even professional drivers (Tzouras et al. 2020). Overall, respondents are not aware of the densities' values; these are only utilized in the modeling process as descriptors of scenarios.

Last but not least, travel time and cost are the variables that mostly affect mode choices. To export the variable levels, in pedestrians, e-scooters, and e-bikes, a fixed speed of 5, 15, and 20 km/h is considered, respectively. Therefore, the deviations in time are due to a higher or lower distance that should be followed by these road users to avoid unsafe interactions with motorized traffic. The variance in car travel times is due to traffic congestion which causes significant delays. Additionally, the prices of existing micro-mobility are considered to define travel cost levels, while the travel cost of walking is fixed at zero.

Model formulation

Two types of models are developed: perceived safety models and mode choice models. Starting (Liddell and Kruschke 2018) with the first model, perceived safety is estimated utilizing two equations that are presented below. In Eq. 1, the latent perceived safety is estimated based on a set of different attributes related to personal characteristics and the road environment. The first part of the equation encloses socio-demographic attributes and travel behavior characteristics that may influence safety perceptions. These parameters cannot be controlled in the survey design process, while the existence of collinearities among characteristics may impede some parameters from being included. Categorical variables are added to the model function using dummy variables to investigate potential non-linearities existing among categories (Daly et al. 2016). The second part contains parameters related to the urban road design and the static objects appearing in the road environment, while in the third part, traffic flow parameters are included (i.e., moving objects). One latent perceived safety function is constructed per transport mode; this means a different set of beta coefficients per transport mode. In Eq. 2, the perceived safety level that varies from 1 to 7 can be estimated using a set of kappa thresholds which also differ per transport mode. Therefore, the formulated perceived safety model can simultaneously be an individual-specific, (urban road) link-specific, and (transport) mode-specific model. To calibrate the model, nineteen (19) beta parameters and six (6) kappa thresholds per transport mode must be estimated. These are the unknown parameters that should be determined based on a set of individuals' perceived safety ratings objecting to minimizing the error term of the perceived safety function.

$$\begin{aligned} & psafe^{*}_{\mathrm{i,m,s}} + \epsilon_{\mathrm{i,m,s}} = \left(\sum_{t=1}^{T} \beta_{soc(t)_{\mathrm{m}}} \times soc(t)_{\mathrm{i}} + \sum_{t=1}^{T} \beta_{beh(t)_{\mathrm{m}}} \times beh(t)_{\mathrm{i}} \right) \\ & +(\beta_{infr_{1,\mathrm{m}}} \times \mathrm{infr}_{1,\mathrm{s}} + \beta_{infr_{2,\mathrm{m}}} \times \mathrm{infr}_{2,\mathrm{s}} + \beta_{infr_{3,\mathrm{m}}} \times \mathrm{infr}_{3,\mathrm{s}} + \beta_{pav_{\mathrm{m}}} \times pav_{\mathrm{s}} \\ & +\beta_{obs_{\mathrm{m}}} \times obs_{\mathrm{s}} + \beta_{crs_{1,\mathrm{m}}} \times crs_{1,\mathrm{s}} + \beta_{crs_{1,m}} \times crs_{1,\mathrm{s}}) \\ & +(\beta_{veh_{\mathrm{m}}} \times veh_{\mathrm{s}} + \beta_{bike_{\mathrm{m}}} \times bike_{\mathrm{s}} + \beta_{ped_{\mathrm{m}}} \times ped_{\mathrm{s}}) \end{aligned} \tag{1}$$

$$psafe_{\mathrm{i,m,s(i)}} = \begin{cases} 1, -\infty < psafe^{*}_{\mathrm{i,m,s(i)}} \leq k_{1,m}, veryunsafe \\ 2, k_{1,m} \leq psafe^{*}_{\mathrm{i,m,s(i)}} \leq k_{2,m} \\ 3, k_{2,m} \leq psafe^{*}_{\mathrm{i,m,s(i)}} \leq k_{3,m} \\ 4, k_{3,m} \leq psafe^{*}_{\mathrm{i,m,s(i)}} \leq k_{4,m} \\ 5, k_{4,m} \leq psafe^{*}_{\mathrm{i,m,s(i)}} \leq k_{5,m} \\ 6, k_{5,m} \leq psafe^{*}_{\mathrm{i,m,s(i)}} \leq k_{6}, m \\ 7, k_{6,m} \leq psafe^{*}_{\mathrm{i,m,s(i)}} < +\infty, verysafe \end{cases} \tag{2}$$

where:

I: set of individuals (i.e., respondents),

M: set of transport modes

$S(i)$: set of scenarios completed by individual i (new order from 1 to $S(i)$),

$psafe^{*}_{\mathrm{i,m,s}}$: latent variable of the perceived safety of individual i using mode m in scenario s,

$psafe^{*}_{\mathrm{i,m,s}}$: latent variable of the perceived safety of individual i using mode m in scenario s,

$\beta_{infr_{1,\mathrm{m}}}, \beta_{infr_{2,\mathrm{m}}}, \ldots, \beta_{ped,m}$: beta parameters of the latent perceived safety function of mode m,

$k_{1,m}, k_{2,m}, \ldots, k_{6,m}$: perceived safety kappa thresholds of mode m,

$\epsilon_{\mathrm{i,m,s}}$: error term

$soc(T)_{\mathrm{i}}$: set of sociodemographic characteristics of individual i,

$beh(T)_{\mathrm{i}}$: set travel behavior attributes of individual i,

$infr_{1,\mathrm{s}}$: 1, if there is an urban road with sidewalks less than 1.5 m wide and without a cycle lane in scenario s – type 1,

$infr_{2,\mathrm{s}}$: 1, if there is an urban road with sidewalks equal to or more than 1.5 m wide and without a cycle lane in scenario s– type 2,

s : 1, if shared space scenario s,– type 3 (all $infr$ parameters equal to 0, if there is an urban road with sidewalks equal to or more than 1.5 m wide and with cycle lane – type 0),

pav_{s}: 1, if the pavement of the urban road is in a good condition scenario s,

obs : 1, if there are obstacles in the road environment scenario s,

$crs_{1,\mathrm{s}}$: 1, if there is an non-signalized zebra pedestrian crossing in the next 200 m of scenario s,

crs : 1, if there is a signalized zebra pedestrian crossing in the next 200 m of scenario s, (all crs parameters equal to 0 if there is no zebra pedestrian crossing in the next 200 m),

veh_{s}: vehicle density in vehicles per km per direction of scenario s,

$bike_{\mathrm{s}}$: bike density in bikes per km per direction of scenario s,

ped_s : number of pedestrians in the road environment (next 50 m) of scenario s,

The utility function of each of the examined transport modes contains only three basic parameters, namely: travel time, cost, and perceived safety (see Eq. 3). While previous studies introduced various parameters related to the road environment in the utility function of micro-mobility modes (Meister et al. 2022; Nigro et al. 2022; Ziemke et al. 2017, 2019), the proposed modeling framework keeps this function as simple as possible. This approach paves the way for its integration in other modeling or simulation tools. Hence, additional significant variables related to the road environment or persons' characteristics have been enclosed in the perceived safety variable that differs per mode, route, and individual. Perceived safety levels below 4 increase the disutility of mode m. Perceived safety is assumed to be constant in all urban road links of route r. Travel time and travel cost are two trip parameters that have been integrated with this utility function. Three beta parameters and an alternative constant per transport mode should be estimated based on a set of choice responses.

$$\begin{aligned} &U_{\mathrm{i,m,s}} = V_{\mathrm{i,m,s}} + \epsilon_{\mathrm{i,m,s}} \\ &= \beta_{0,m} + \beta_{time_{\mathrm{m}}} \times time_{\mathrm{m},s} + \beta_{cost_{\mathrm{m}}} \\ &\times cost_{\mathrm{m,s}} + \beta_{psafe_{\mathrm{m}}} \times (psafe_{\mathrm{i,m,s}} - 4) + \epsilon_{\mathrm{i,m,s}} \end{aligned} \tag{3}$$

where:

$U_{\mathrm{i,m,s}}$: utility of using mode m in first/last by individual i in scenario s,

$V_{\mathrm{i,m,s}}$: systematic utility of using mode m in first/last by individual i in scenario s,

$\beta_{time_{\mathrm{m}}}, \beta_{cost_{\mathrm{m}}}, \beta_{psafe_{\mathrm{m}}}$: beta parameters of the utility function of mode m;

$\epsilon_{\mathrm{i,m,s}}$: error term

$\beta_{0,m}$: alternative specific constant of mode m,

$time_{\mathrm{m},s}$: travel time of using mode m in scenario s,

$cost_{\mathrm{m,s}}$: travel cost of using mode m in scenario s,

The common utility function can have a distance reference. This can be achieved by integrating factors related to the travel speed and the monetary distance rate of each transport mode. A simple mathematical transformation of the model is presented above:

$$\begin{aligned} U_{\mathrm{i,m,s}}(d) &= \beta_{0,m} + \beta_{time_{\mathrm{m}}} \times \frac{d}{v_m} + \beta_{cost_{\mathrm{m}}} \times cd_m * d + \beta_{psafe_{\mathrm{m}}} \times (psafe_{\mathrm{i,m,s}} - 4) + \epsilon_{\mathrm{j,r,m}} \\ &= [\beta_{0,m} + \beta_{psafe_{\mathrm{m}}} \times (psafe_{\mathrm{i,m,s}} - 4)] + \left(\frac{\beta_{time_{\mathrm{m}}}}{v_m} + \beta_{cost_{\mathrm{m}}} \times cd_{r,m}\right) * d + \epsilon_{\mathrm{j,r,m}} \end{aligned} \tag{4}$$

where:

d : travel distance factor,

v_m : average travel speed of transport mode m; it is not always constant and can be influenced by traffic conditions,

$cd_{r,m}$: the monetary distance rate of transport mode m in route r; this can be influenced by multiple factors such as energy consumption, pricing schemes of shared mobility services, etc.

The Value-of-Safety (VoS) shows how many kilometers of less traveling are people willing to exchange to experience one more level of perceived safety. The VoS requires the use of a fixed travel speed and distance rate. This can be defined as:

$$VoS_m = \frac{\beta_{psafe_{\mathrm{m}}}}{\beta_{d_m}} = \frac{\beta_{psafe_{\mathrm{m}}}}{\left(\frac{\beta_{time_{\mathrm{m}}}}{v_m} + \beta_{cost_{\mathrm{m}}} * cd_m\right)} \tag{5}$$

Survey design

Since there are many variables, complicated models, and a double-stated preference experiment with scenes and images, the survey design process requires further attention. Figure 2 presents its steps through an analytical methodological flow diagram.

In general, the methodology is based on two fractional factorial designs which should be matched. Starting with the design of the rating experiment, the total number of scenarios that can be formulated is $4 * 2 * 2 * 3 * 3 * 3 = 432$. To minimize the number of scenarios, an orthogonal table that ensures zero correlations among the selected independent variables is utilized in the end (Hensher 1993). The output table contains 36 rows, therefore 36 scenarios which are divided into 3 blocks of questions. This division is applied to minimize the time required to complete the survey. Hence, each respondent rates perceived safety considering only 12 scenarios.

Simultaneously, four (imaginary) scenes are created; these scenes refer to four types of infrastructure described in the above paragraphs (see also Fig. 1). The Greek Urban Road Design principles were fully respected to create these scenes (Hellenic Ministry of Infrastructure and Transport 2015, 2001). To ensure homogeneity in terms of road aesthetics, it was decided to add trees on sidewalks wider than 1.5 m, as is commonly done in Athens, Greece. Thus, only type 1 does not have road vegetation; this case is fully dominated by motorized traffic. Next, based on the developed scenarios, several modifications to these scenes were performed by adding static (i.e., obstacles, “zebra” pedestrian crossings) and moving objects (cars, bicycles, and pedestrians). Since moving objects, such as cars can obstruct the view of static objects like “zebra” pedestrian crossings a reasonable assumption was made: Cross-sections featuring pedestrian crossings were simultaneously equipped with complete horizontal signage. Besides, the absence of zebra crossings in a unidirectional street is typical indicative of inadequate maintenance in road markings. The pavement condition was illustrated in the images by adding some cracks or changing the color of the

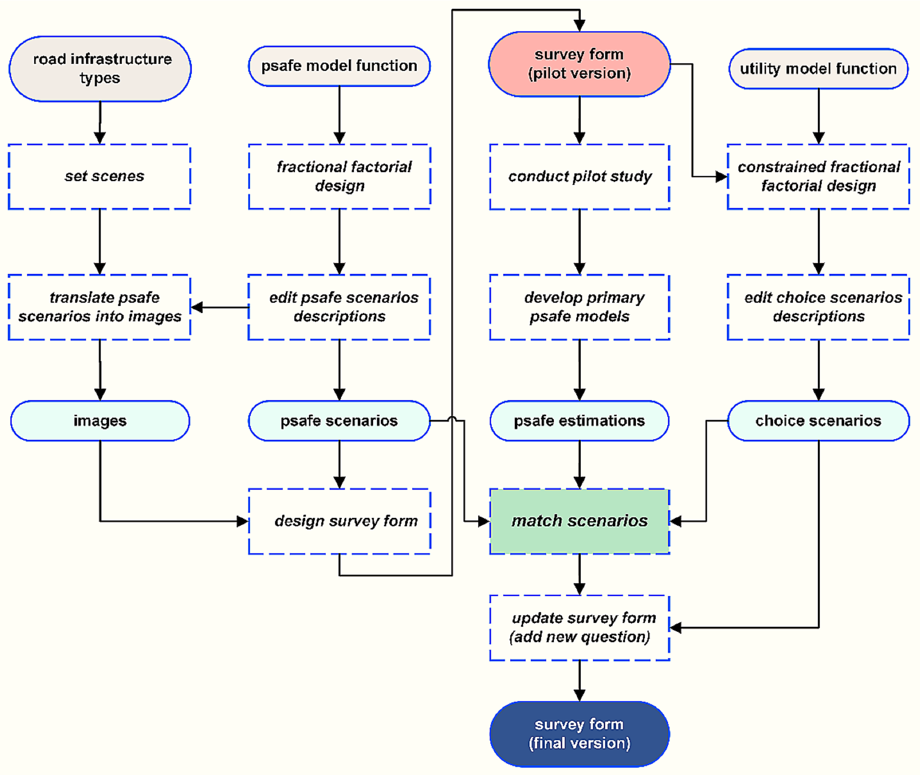

Fig. 2 Methodological flow diagram of the survey design process

asphalt. Perceived safety scenarios were also described with explanatory text below the images. To quantify perceived safety, respondents are asked to answer a simple question, namely: *"How safe would you feel on this road?*. Respondents rate perceived safety per transport mode. Therefore, four ratings are provided by each respondent using this methodological tool. A sample scenario is given in **Appendix A**.

The design of the second stated preference experiment is constrained by the first one. The main objective of this process is not only to find scenarios that ensure zero correlation among the independent variables, but their total number is a factor of or equal to the total number of perceived safety scenarios. In other words, the choice scenarios should be matched with at least one perceived safety scenario. The variables included in Eq. 3 are introduced. In this case, perceived safety is the independent variable; thus, the orthogonal design indicates the perceived safety level that should be added per choice scenario. Consequently, perceived safety per image and transport mode was estimated first by considering primary safety evaluations provided by 10 experts from the transportation planning discipline. Considering the prior beta parameters and thresholds, the scenarios were matched, so that the correlation between perceived safety and other variables of the utility function be minimized. The final survey design table contains a positive correlation of 0.06 between perceived safety and travel time and a negative one of -0.07 between perceived safety and travel cost. Based on this table, the pilot survey form was updated by adding an extra question that connects both parts of the survey form: *"Your daily route consists of urban roads with traffic conditions like above. Which transport mode would you select, if you were aware of the travel time and cost you are going to spend?"*. It is evident that this double-stated preference experiment does not assess driving behavior on an operational or tactical level. Respondents are not queried about their potential reactions in terms of accelerating/decelerating or maneuvering to cope with mixed traffic conditions presented in the images of the experiment This would require a more refined presentation of the depth dimension which refers to the spatial extent or distance between objects along the third axis.

In the survey, certain conditions remained consistent across all scenarios for every respondent, ensuring that their choices held significance within the context of the study. These conditions were explicitly outlined in the survey introductory text. The fundamental assumptions that guided the experiment are: The maximum trip length was constrained to 4 km/h including the necessary detours to avoid congestion or unsafe discontinuities. The trip is to the nearest metro station within their urban area; there are parking facilities for all vehicle types in these endpoints. Outside their residences, shared e-scooters and e-bikes are accessible, albeit with associated service costs. Last, each respondent possessed access to one car for commuting to the closest train station. Therefore, all transport options can ensure a direct trip to the closest station without additional time to find a vehicle or a parking spot.

Model specification

To estimate the unknown parameters of the perceived safety model, an ordinal logistic regression is performed. The ordinal logistic regression (or ordered logit) is based on the proportional odds assumption, which means that the odds ratio remains constant for all the different intervals configurated from the selected Likert Scale (Liddell and Kruschke 2018; Scott Long 2015). Therefore, there is only one set of beta coefficients per interval to estimate the latent variable (Tzouras et al. 2020). In ordered logit models, the value of the odds ratio can be interpreted as: for a unit increase in x the odds of being in a perceived safety level equal to or less than or n change by a fixed factor exp(-b) (Tzamourani et al. 2022). The validity of the proportional odds assumption can be tested by performing a X^2 test. If it is found to be invalid, then the dependent ordinal variable should be treated as nominal utilizing classical modeling techniques, such as binary logit or multinomial logit. Below, the probability function of the ordinal logit mode is presented (i.e., Eq. 6). To capture heterogeneity in safety perceptions among individuals, random beta variables are particularly integrated when addressing variables related to the road environment. Nevertheless, the data are panelized which means that there are serious dependencies in the ratings provided by each respondent (Chorus et al. 2013).

$$
\begin{aligned}
&P\left(psafe_{\mathrm{i,m,s(i)}}=\mathrm{n}|X\right)=P\left(psafe^{*}_{\mathrm{i,m,s}}\leq k_{\mathrm{n,m}}\right)-P\left(psafe^{*}_{\mathrm{i,m,s}}+\leq k_{\mathrm{n-1,m}}\right)\\
&=F\left(k_{\mathrm{n,m}}-\sum_t\beta_{x_r(t),m}\times x_r(t)_{s(i)}+\sum_t\beta_{x_f(t),m}\times x_f(t)_s\right)\\
&-F\left(k_{\mathrm{n-1,m}}-\sum_t\beta_{x_r(t),m}\times x_r(t)_{s(i)}+\sum_t\beta_{x_f(t),m}\times x_f(t)_s\right)\\
&=\frac{\exp\left(k_{n,m}-\sum_t\beta_{x_r(t),m}\times x_r(t)_s+\sum_t\beta_{x_f(t),m}*x_f(t)_s\right)}{1+\exp\left(k_{n,m}-\sum_t\beta_{x_r(t),m}\times x_r(t)_s+\sum_t\beta_{x_f(t),m}\times x_f(t)_s\right)}\\
&-\frac{\exp\left(k_{n-1,m}-\sum_t\beta_{x_r(t),m}\times x_r(t)_s+\sum_t\beta_{x_f(t),m}\times x_f(t)_s\right)}{1+\exp\left(k_{n-1,m}-\sum_t\beta_{x_r(t),m}\times x_r(t)_s+\sum_t\beta_{x_f(t),m}\times x_f(t)_s\right)}
\end{aligned}
\tag{6}
$$

where:

F : cumulative logistic distribution function $\left(F\left(x\right)=\frac{1}{1+\exp(-x)}\right)$

$\beta_{xr.m}$: set of random beta variables of perceived safety model of transport mode m,

$\beta_{xf,m}$: set of fixed beta variables of perceived safety model of transport mode m,

k_n : perceived safety kappa thresholds of mode m of level n (where $k_0=-\infty$ and $k_7=+\infty$).

This study implements a Simulated Maximum Likelihood Estimation (MLE) method to compute panel effects and random beta parameters. The maximization of the joint probability is achieved through a Monte-Carlo Simulation using a pre-specified number of Halton draws. In the end, both fixed unknown variables and the normal distribution of the random ones are exported. The joint probability function to estimate the perceived safety level is:

$$maximizeL=\int\left\{\prod_{s=1}^{S(i)}\prod_{n=1}^{N-1}\left[P(psafe_{\mathrm{i,m,s}}=\mathrm{n}|X)^{y_{\mathrm{i,m,s}}(n)}\right]\right\}\times\prod_{t=1}^{T}g\left(\beta_{x_r(t),m}\right)\times d\beta_{x_r(t),m} \tag{7}$$

where:

L : likelihood

$y_{\mathrm{i,m,s}}\left(n\right)$: 1, if perceived safety level n of using mode m is chosen by individual i in scenario s,

$g\left(\beta_{x_r(t),m}\right)$:normal probability density function which describes random variable $\beta_{x_r(t),m}\sim N(\overline{\beta_{x_r(t),m}},\sigma_{\beta_{x_r(t),m}})$

Binary logistic regression (binary logit) has been utilized in the past to estimate marginal utilities and different values which can describe the willingness of one traveler to use a new transport mode (Kepaptsoglou et al. 2020; Sorkou et al. 2022) or to choose a particular path (Rossetti and Daziano 2022; Saplıoğlu and Aydın 2018). In this study, binary logit is applied to approach the VoS based on the estimated betas per transport mode. The VoS was defined above in Eq. 5. Mode choices can be converted to a binary variable (0 or 1) developed for each transport mode: i.e., to use or not. The probability function of a binary logit model is simpler compared to the one of the ordered logit (see Eq. 7). It gives the chance that the systematic variation of the utility is greater than the error. Again, to capture panel effects, some beta parameters are selected to be random.

$$P\left(\epsilon_{\mathrm{i,m,s}}\leq V_{\mathrm{i,m,s}}|X\right)=\frac{\exp\left(\sum_t\beta_{x_r(t),m}\times x_r(t)_s+\sum_t\beta_{x_f(t),m}\times x_f(t)_s\right)}{1+\exp\left(\sum_t\beta_{x_r(t),m}\times x_r(t)_s+\sum_t\beta_{x_f(t),m}\times x_f(t)_s\right)} \tag{8}$$

$\beta_{xr.m}$: set of random beta variables of utility function of transport mode m,

$\beta_{xf,m}$: set of fixed beta variables of utility function of transport mode m,

A double Monte Carlo simulation is applied to estimate the VoS. The first one is based on a Simulated MLE similar to the one applied above, based on which the normal distributions of the random beta variables can be determined. Next, the random beta variables are utilized to plot distributions of VoS.

$$maximizeL = \int \left\{ \prod_{s=1}^{S(i)} \left[P(\epsilon_{\mathrm{i,m,s}} \leq V_{\mathrm{i,m,s}}|X)^{y_{\mathrm{i,s}}(m)} \right] \right\} \times \prod_{t=1}^{T} g\left(\beta_{x_r(t),m}\right) \times d\beta_{x_r(t),m} \quad (9)$$

where:

$y_{\mathrm{i,s}}(m)$: 1, if mode m is chosen by individual i in scenario s.

In the last step, mixed logit is preferred to develop models that describe the first/last mode choice model taking safety perceptions into account. As a technique, panel mixed logit considers not only dependencies among the choices of a respondent but also dependencies that may exist among provided travel options (Molin et al. 2009). This is often called the "red-blue bus problem" (Ben-Akiva and Bierlaire 1999) which leads to overestimated probabilities. To test this, the Alternative Specific Constant (ASC) of each transport mode is selected to be random. In other respects, the logit probability function of the discrete choice model is nothing more than an upgraded version of the binary logit function; a similar estimation technique is used at the end (see Eqs. 8 and 9).

$$P\left(V_{\mathrm{i,m,s}} + \epsilon_{\mathrm{i,m,s}} > V_{\mathrm{i,p,s}} + \epsilon_{\mathrm{i,p,s}}|X\right) = \frac{\exp\left(\beta_{0,m} + \sum_t \beta_{x_r(t),m} * x_r(t)_s + \sum_t B_{x_f(t),m} * x_f(t)_s\right)}{\sum \exp\left(\beta_{0,m} + \sum_t \beta_{x_r(t),m} * x_r(t)_s + \sum_t B_{x_f(t),m} * x_f(t)_s\right)} \quad (10)$$

$$maximizeL = \int \left\{ \prod_{s=1}^{S(i)} \left[P(V_{\mathrm{i,m,s}} + \epsilon_{\mathrm{i,m,s}} > V_{\mathrm{i,p,s}} + \epsilon_{\mathrm{i,p,s}}|X)^{y_{\mathrm{i,s}}(m)} \right] \right\} \times \prod_{t=0}^{T} g\left(\beta_{x_r(t),m}\right) \times d\beta_{x_r(t),m} \quad (11)$$

All the models are estimated using the newest version of the open-source Python package Pandas Biogeme (i.e., 3.2.10) developed and maintained by Prof. M. Bierlaire at Ecole Polytechnique Fédérale de Lausanne (EFPL), Switzerland (Bierlaire 2019).

Participants and procedure

The questionnaire form was uploaded on the QuestionPro platform. It was available only online so that all respondents would experience images before rating perceived safety. As has been mentioned, a pilot study with 10 academic transport planning experts was conducted to test and improve the effectiveness of this methodological in capturing safety perceptions. They reviewed the survey form and submitted recommendations for further improvements. The sequence of scenarios was one point, which required more attention. To familiarize the respondent with the different scenes, each of the four infrastructure types (from type 0 to type 3) was presented in the four first scenarios of the survey. The next scenarios were randomly mixed per block and presented. Moreover, effective ways to connect the two stated preferences experiments without creating multicollinearities were discussed with the experts. As they noted, this part of the applied methodology comprises a very sensitive point. Lastly, block randomization was applied to ensure an equal number of observations per block and therefore almost zero correlations among independent variables.

Members of the academic community (faculty members, students etc.) residing in Athens, Greece (i.e., undergraduate, postgraduate, and Ph.D. students) were invited to fill out the survey via messages from social media and e-mails. The response rate was relatively high, approximately 83%. University students are considered potential micro-mobility users, as they are young and exhibit high familiarization with various technological advancements and smartphone applications (Sorkou et al. 2022). Furthermore, e-bikes and e-scooters are foreseen as an effective solution to connect the university campuses with the nearest Metro Stations creating car-independent areas, as previous studies have shown (Bai and Jiao 2020; Moosavi et al. 2022; Sanders et al. 2020b). Yet only 1% of university students choose to use a micro-mobility mode to reach NTUA (Kopsidas et al. 2019). In Athens, approximately 40% of trips covering less than 5 km are undertaken by private cars despite the high spatial coverage of bus services (Kepaptsoglou et al. 2015; Milakis et al. 2008; Tzamourani et al. 2022). Only, the 23% of these trips are accomplished by walking (Chatziioannou et al. 2023). These insights reveal the first/last mile problem still exists in Athens and has prompted new studies exploring innovative solutions for Athens such as DRT, e-scooters, and other shared mobility options (Charisis et al. 2018; Liazos et al. 2022; Triantafillidi et al. 2023). Therefore, the experiment explores the main reason why young people choose to not cycle (or "scoot") in Athens by estimating models which are useful for the local community as well.

Results

In total, 129 people participated in the experiment. Among them, 67 (51.9%) are male and 62 (48.1%) were female. 71% belonged to the 18 to 30 age group, while 64% of the sample were university students or graduates of NTUA. The declared average monthly net income of the respondents was estimated at approximately 1250€. Only 4.7% (6/129) of respondents does not have a driving license. Simultaneously, 96.9% of the respondent stated that their households own a car. Yet only 43.1% of them use it daily; This contradiction suggests that some participants are seeking flexible alternatives to avoid heavy daily traffic. But it is noteworthy that 6% of the respondents owned a micro-mobility transport mode, e.g., e-scooter, e-bike, or conventional bicycle, etc. This group uses the private micro-mobility modes at least once a week, while the rest 94% of respondents either use a micro-mobility mode once a year (56%) or once a month (33%). The mobility patterns described above align with those previously highlighted ones in the preceding section. As inferred, the majority lack experience in navigating urban roads in Athens using e-bikes or e-scooters. The final dataset contained 5771 observations of perceived safety and 1417 choice responses. By conducting an Analysis of Variance (ANOVA), only gender, age group (younger than 30, or not), and the possession of driving license can be considered as statistically significant socio-demographic determinants of perceived safety rates. Among them, there were weak and insignificant correlations. That is why, these variables were taken into considering in the modeling process.

Perceived safety models

In the next step, the perceived safety models were developed. The median value of perceived safety was estimated to be equal to 5; yet there were some notable differences among transport modes that should be discussed. In approximately 50% of scenarios, respondents scored the safety perceptions of riding an e-scooter with the lowest possible value, i.e., "1: very unsafe". On the contrary, walking and car driving were evaluated by respondents with the highest safety scores in around 40.1% and 34.1% of cases, respectively. Age had a significant contribution to the ratings of safety perceptions, as the median safety score provided by young people (under 30) was 5/7, while in older groups, the median fell to 4/7 considering all transport modes. Additionally, females felt more unsafe in most scenarios, as indicated by the average scores per social group, i.e., 4.49/7 for males and 4.29/7 for females. Lastly, respondents with driving licenses tended to provide higher perceived safety rates; however, the sample of the no-driving license group was relatively small to extract valid conclusions. Figure 3 illustrates the above-described statistical trends.

The type of road infrastructure significantly influenced the mean perceived safety scores. In type 0, the mean scores were 5.31/7 for car driving, 5.54/7 for e-bike riding, 4.93/7

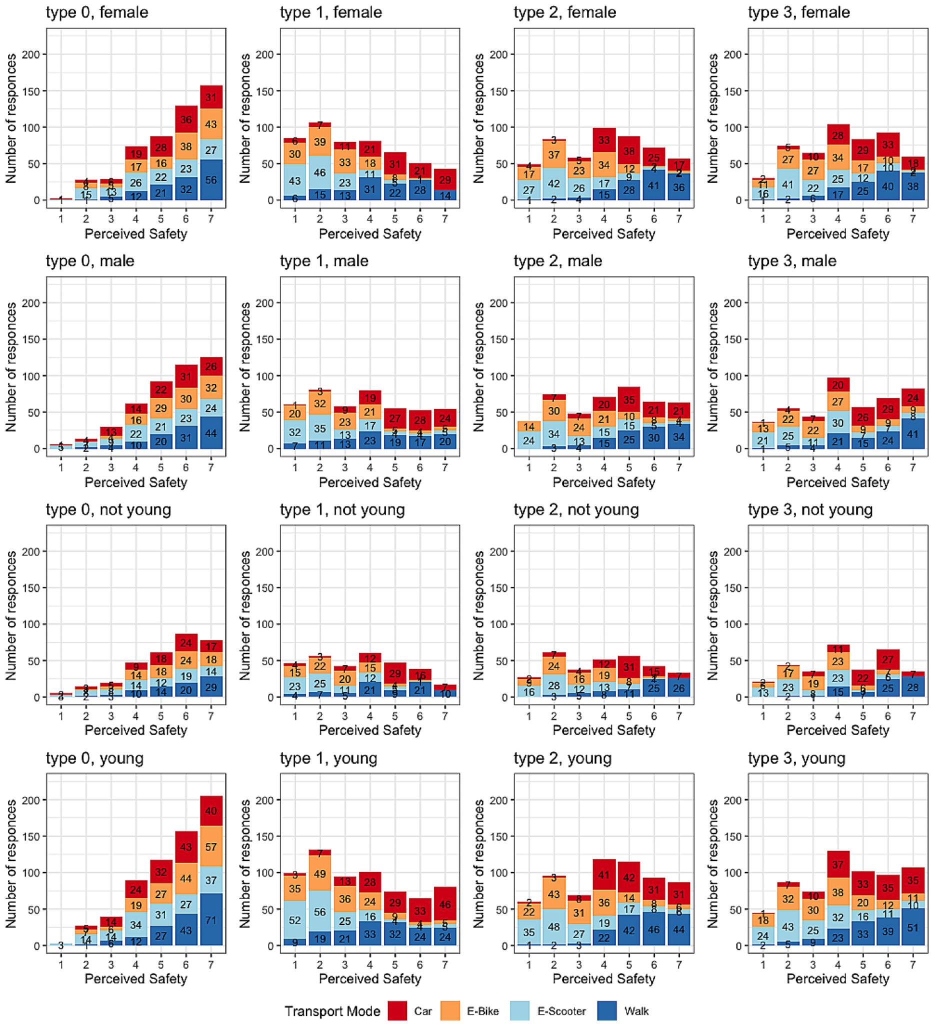

Fig. 3 Stacked bars that present perceived safety ratings per transport mode and social group (mentioned in the chart title)

for e-scooter riding, and 5.82/7 for walking. A notable decrease was observed in type 1. Specifically, the mean scores for e-bike and e-scooter riding dropped to 2.68 and 2.40/7, respectively. However, the mean score for car driving remained constant at 5.17/7. Types 2 and 3 presented almost identical scores. However, there was a significant deviation in e-bike riding, as the shared space scenario was rated higher than the type 2 scenario by an average of + 0.58. Moreover, high vehicle or pedestrian density reduced the chance a respondent will rate the perceived safety of car driving with the highest score, i.e., 7. The perceived safety of e-bike riding was more affected by vehicle density, while for e-scooter riding, no correlation was observed. Walkers' perceived safety was downgraded in scenarios that the bikes' density exceeded 50 bikes/km/dir according to survey responses. The impact of mixed traffic conditions on perceived safety ratings is presented in Fig. 4.

A Kendall correlation test is applied to test potential multicollinearities existing especially among socio-demographic and travel behavior characteristics. The correlation analysis confirmed that there were no significant correlations for a 95% confidence interval. Next, the proportional odds assumption is investigated by applying a X^2 comparing a model using the proportional odds assumption (null hypothesis) with one not using it. For a 95% confidence interval, it is valid for the perceived safety model of e-bike and e-scooter. Yet, the proportional odds assumption was not met perceived safety models for private cars and walking. This means that a binary logit or a multinomial logit model would represent more appropriately perceived safety scores. Therefore, scenarios could be better classified into only two categories: safe or not safe for car driving/walking. This is interesting as it shows the differences existing among safety perceptions. This output validates the applicability of the proposed modeling framework for micro-mobility modes. However, it also prompts us

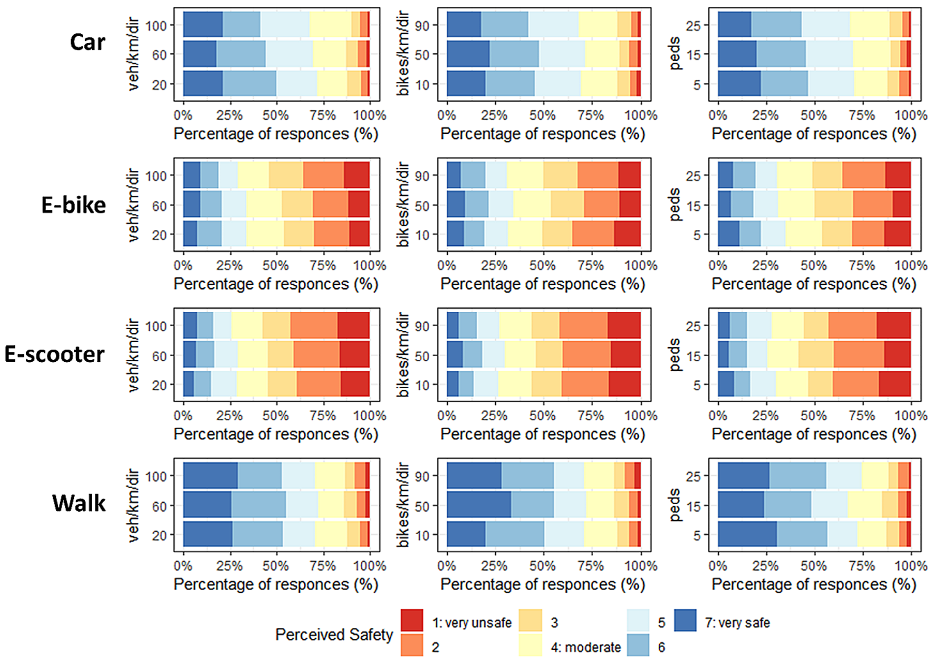

Fig. 4 Horizontal 100% stacked bars that present the impact of each traffic condition variable on perceived safety ratings per transport mode

Table 3 Perceived safety models (all statically significant variables per mode for 95% confidence interval are indicated with * next to the probabilities)

	Car			E-bike			E-scooter			Walk		
	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)
Gender (1, if male)	0.622	0.235	0.008*	0.349	0.215	0.104	0.408	0.230	0.076	-0.055	0.246	0.823
Age group (1, if < 30 years old)	0.707	0.252	0.005*	0.758	0.229	0.001*	0.739	0.248	0.003*	0.455	0.260	0.080
Driving license (1, if yes)	2.678	0.762	< 0.001*	0.221	0.714	0.757	-0.320	0.936	0.733	2.266	0.630	< 0.001*
With pedestrian crossings, not controlled by traffic lights (1, if yes)	-0.780	0.130	< 0.001*	-0.458	0.136	0.001*	-0.565	0.137	< 0.001*	-1.702	0.142	< 0.001*
With pedestrian crossings controlled by traffic lights (1, if yes)	0.023	0.129	0.858	0.052	0.135	0.701	0.056	0.135	0.678	0.030	0.132	0.818
With good pavement condition (1, if yes)	1.447	0.127	< 0.001*	0.918	0.115	< 0.001*	1.043	0.119	< 0.001*	0.258	0.118	0.028*
Without obstacles (1, if yes)	0.236	0.115	0.040*	0.408	0.108	< 0.001*	0.549	0.114	< 0.001*	1.065	0.119	< 0.001*
Vehicle density (veh/km/dir)	-0.002	0.002	0.480	-0.005	0.002	0.017*	-0.002	0.002	0.322	0.002	0.002	0.334
Bike density (bikes/km/dir)	-0.001	0.002	0.434	0.000	0.002	0.827	-0.002	0.002	0.417	0.004	0.002	0.050*
Pedestrians in the road env (peds)	-0.005	0.010	0.584	-0.009	0.008	0.257	-0.004	0.008	0.625	0.006	0.009	0.503
Infrastructure type – Mean values												
Urban road with sidewalks < 1.5 m wide (1, if yes)	-0.840	0.188	< 0.001*	-5.649	0.286	< 0.001*	-4.531	0.278	< 0.001*	-2.466	0.204	< 0.001*
Urban road with sidewalks > 1.5 m wide (1, if yes)	-0.781	0.154	< 0.001*	-4.801	0.257	< 0.001*	-3.410	0.214	< 0.001*	-0.909	0.162	< 0.001*
Shared space (1, if yes)	-0.937	0.167	< 0.001*	-3.930	0.256	< 0.001*	-2.738	0.228	< 0.001*	-0.521	0.170	0.002*
Infrastructure type – Std. Dev. values												
Urban road with sidewalks < 1.5 m wide	0.745	0.232	0.001*	1.797	0.201	< 0.001*	1.609	0.225	< 0.001*	0.917	0.207	< 0.001*
Urban road with sidewalks > 1.5 m wide	0.124	0.403	0.759	1.679	0.180	< 0.001*	1.195	0.256	< 0.001*	0.504	0.304	0.097
Shared space	0.321	0.402	0.425	1.958	0.216	< 0.001*	1.449	0.241	< 0.001*	0.471	0.279	0.092
kappa 1	-2.927		< 0.001*	-6.720		< 0.001*	-4.960		< 0.001*	-4.133		< 0.001*
kappa 2	-1.315		< 0.001*	-4.259		< 0.001*	-2.518		< 0.001*	-2.400		< 0.001*
kappa 3	-0.195		< 0.001*	-2.649		< 0.001*	-1.295		< 0.001*	-1.242		< 0.001*
kappa 4	1.643		< 0.001*	-0.859		< 0.001*	0.103		< 0.001*	0.423		< 0.001*
kappa 5	3.351		< 0.001*	0.497		< 0.001*	1.372		< 0.001*	1.788		< 0.001*
kappa 6	5.433		< 0.001*	2.232		< 0.001*	2.848		< 0.001*	3.758		< 0.001*
Number of observations	1443			1443			1443			1443		
Number of individuals	129			129			129			129		

Table 3 (continued)

	Car			E-bike			E-scooter			Walk		
	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)
Null loglikelihood (zero-coefficients)	-2777			-2845			-2933			-2951		
Loglikelihood at convergence	-2065			-2191			-2231			-2054		
Halton draws	2000			2000			2000			2000		

to reassess its universality to conventional transport modes. In the next steps, ordered logistic regression was still used of the modeling process; this allowed the authors to make meaningful comparisons regarding the contribution of the road environment in perceived safety.

The model outputs are presented in Table 3. Starting with the perceived safety of car driving, all infrastructure types, the existence of obstacles, and pavement were found to be statistically significant for a 95% confidence interval. Unexpectedly, the beta parameter of the dummy variable referring to the presence of a non-signalized pedestrian crossing was significant and had a negative value in all transport modes (car: -0.780, e-bike: -0.458, e-scooter: -0.565 and walk: -1.702 utils), while a signalized pedestrian crossing had insignificant difference compared to the complete absence of pedestrian crossings and road markings. E-bike use was found to be significantly affected by the density of car traffic, (-0.005 utils/veh/km*dir). All infrastructure type parameters had negative values. This indicates that type 3 was considered the safest, both for e-bike and for e-scooter riding. E-scooter users did not appear to be influenced by the surrounding traffic flows, while pedestrian safety was found to be affected by a high density of bikes (-0.005 utils/bikes/km*dir). Overall, road users' safety perceptions were not influenced by those who belong to the same category of road users, e.g., safety perceptions of walking by the number of pedestrians in the image.

In the estimation of perceived safety models, the beta parameters of the dummy variables of the infrastructure type were selected to be random. Figure 5 visualizes the heterogeneity existing among the safety perceptions of individuals, where beta coefficients with insignificant standard deviation are represented by vertical lines. Focusing on the mean values, shared space was perceived as a safer cross-section design to ride an e-bike, e-scooter, or to walk (car: -0.937, e-bike: -3.930, e-scooter: -2.738 and walk: -0.521 utils) in comparison to type 1 (car: -0.840, e-bike: -5.649, e-scooter: -4.531 and walk: -2.466 utils) and type 2 (car: -0.154, e-bike: -4.801, e-scooter: -3.410 and walk: -0.909 utils). At the same time, the heterogeneity in opinions of individuals about this unconventional design were lower compared to type 1 which is the highest in all transport modes, except e-bikes.

Mode choice models

In these models, perceived safety was considered as an explanatory variable of travel behavior. Perceived safety model predictions were used in this step. The simulated MLE processed the perceived safety rates provided by each respondent in each scenario using each transport mode. Hence, the two modeling processes are independent of each other.

A binary logistic regression per transport mode is performed to model the willingness to use each transport mode. Travel time, cost, and perceived safety were selected to be random. The results of this process are shown in Table 4. As can be seen, in all cases perceived safety was a statistically significant variable with a positive value, which means that the higher it is, the higher the willingness to use this transport mode. Interestingly, the beta parameter of travel time related to e-bike use was found to be positive, i.e., 0.020 utils/min, while its standard deviation was insignificantly different than zero with 95% confidence. This means that there is a high level of agreement among individuals. Additionally, the ASC of the e-bike binary logit model was found to be insignificant too; thus, the unwillingness of travelers to use e-bike can be well explained by parameters like the service cost and the perceived safety of the selected route. The model referring to the selection of e-scooters to perform daily first/last mile trips reported the highest McFadden's Rho, i.e., 0.546. Indeed, there was a high

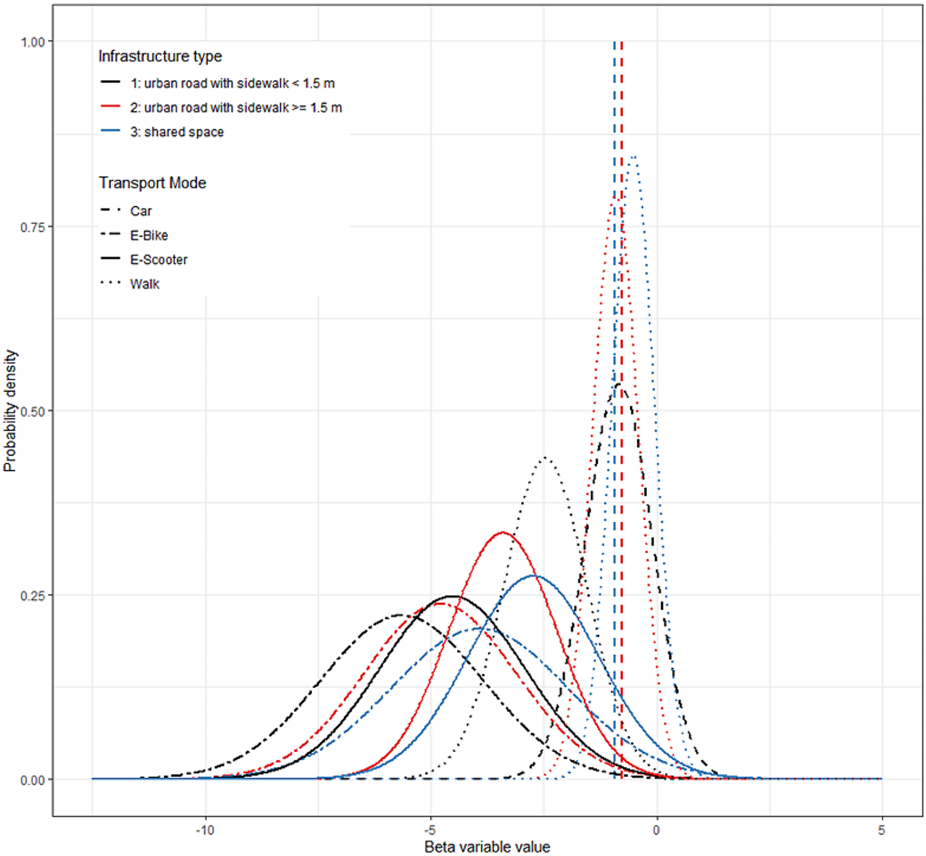

Fig. 5 Normal distributions of infrastructure type random beta parameters per transport mode

level of agreement among individuals, as the standard deviation of the perceived safety beta parameter was insignificant. Compared to e-bikes, beta parameters of travel time and cost were estimated to be negative. In walking, the lowest mean value of the perceived safety coefficient was reported in the models' results, namely: car: 0.298, e-bike: 0.636, e-scooter: 0.431, and walk: 0.119 utils/lev.

To approach Value-of-Safety (VoS) by importing random and non-random parameters, a new Monte-Carlo simulation was performed. It uses 20,000 draws from normal distributions with the parameters defined in the binary logistic regression models. The constant speed and cost rates were used, namely: car: 40 km/h and 0.15 EUR/km, e-bike: 20 km/h and 0.75 EUR/km, e-scooter: 15 km/h and 0.94 EUR/km and walk: 5 km/h and 0 EUR/km. The outputs of this analysis are presented in Fig. 6; descriptive statistics are also provided in the legend. In car driving, the mean VoS was estimated at -2.64 km/lev. This means that car drivers were willing to exchange 2.64 km of less traveling to experience one more safety level. In e-bike riding, one safety level was exchanged for 2.61 km. The VoS of e-scooter riding was much lower, at approximately -660 m, while the standard error did not exceed 3 m. Lastly, pedestrians exchanged only 180 ± 3.2 m of less traveling to follow a safer path (+1 safety level).

Table 4 Binary logit (BL) willingness to use choice models with random beta parameters (all statically significant variables per mode for 95% confidence interval are indicated with * next to the probabilities)

	BL route model - Car			BL route model E-bike			BL route model E-scooter			BL route model Walk		
	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)
Alternative specific constant	1.880	0.300	<0.001*	0.0031	0.225	0.890	-0.475	0.230	0.039*	1.080	0.176	<0.001*
Mean values												
Travel time in minutes	-0.045	0.006	<0.001*	0.020	0.009	0.028*	−0.042	0.013	0.008*	-0.066	0.007	<0.001*
Travel cost in euros	-0.410	0.057	<0.001*	−0.456	0.063	<0.001*	-0.606	0.109	<0.001*			
Perceived safety in levels	0.298	0.061	<0.001*	0.636	0.081	<0.001*	0.431	0.064	<0.001*	0.119	0.056	0.036*
Std. Dev. values												
Travel time in minutes	0.032	0.008	<0.001*	0.003	0.012	0.782	0.043	0.011	<0.001*	−0.025	0.005	<0.001*
Travel cost in euros	0.124	0.040	0.039*	0.117	0.062	0.057	0.143	0.104	0.167			
Perceived safety in levels	0.085	0.0701	0.224	0.613	0.096	<0.001*	0.049	0.075	0.506	-0.139	0.064	0.027*
Number of observations	1417			1417			1417			1417		
Number of individuals	120			120			120			120		
Null loglikelihood	-982.2			-982.2			-982.2			-982.2		
Loglikelihood at convergence	-811.5			-660.9			-455.9			-563.7		
McFadden's Rho	0.174			0.327			0.546			0.426		
Halton draws	5000			5000			5000			5000		

The last step refers to the estimation of the Mixed Logit model using 5000 Halton draws to describe mode choices in first/last mile trips (see Table 5). To consider dependencies among alternatives, both the ASCs and the beta parameters of perceived safety were selected to be random. Based on the results, there was significant heterogeneity among individuals in transport mode preferences, as demonstrated by the significant standard deviations of constant coefficients. Nevertheless, in e-bike and e-scooter riding, the mean ASC values were found to be insignificantly different to zero. Travel time and cost were significant variables with negative beta parameters. The McFaddens' Rho was estimated to be equal to 0.336.

Discussion

According to the survey results, e-scooter appeared to be perceived as a less safe mode in most road environments presented to the respondents. The e-bike comes next in this classification, followed by walking and car. This is in line with previous studies that identified that safety concerns and discomfort severely limit the utility of e-scooters compared to e-bike (Bai et al. 2017b; Kopplin et al. 2021). Females scored the perceived safety of micro-mobility modes (i.e., e-bikes and e-scooters) with lower rates in comparison to males. This was an expected result, as previous studies also noted the tendency of women to underate perceived safety (Akgün-Tanbay et al. 2022; Fitch et al. 2022; Hidayati et al. 2020). According to the model outputs, individuals aged over 30 may not adopt micro-mobility modes, and specifically e-scooters, since they do not feel safe enough to ride in complex urban road environments. This study focused on the concerns of inexperienced micro-mobility users coming from Athens, Greece, revealing that the absence of specialized cycling infrastructure can explain their unwillingness to change travel behavior. Indeed, all road users rated the design that proposed the full segregation of traffic flows (i.e. type 0) more highly. As opposed to infrastructure types 1 and 2, which give more space to motorized traffic, the addition of a cycle lane ensures the right balance between active modes and vehicle traffic in terms of safety perceptions. This is confirmed by previous studies about cycling safety, which concluded that exclusive or semi-exclusive cycle lanes are more effective in changing the mobility habits of travelers, as they are perceived as safer than mixed-traffic design proposals (Branion-Calles et al. 2019; Calvey et al. 2015; Chataway et al. 2014; Reggiani et al. 2022). However, the limited availability of public space is an additional parameter that should be considered before finally answering the *"to share or to segregate?"* dilemma, posed by Tsigdinos et al. (2022). To this end, shared space can be seen as a middle-ground solution for all road users. This also aligns with the findings of Martínez-Díaz and Arroyo (2023), who reported certain positive effects but lacked definitive impacts of the traffic calming design approach. Interestingly, homogeneity in opinions of individuals regarding the contribution of shared space to perceived safety was relatively higher compared to designs where motorized traffic dominates. This consensus could allow the co-existence of road users leading simultaneously to a more homogenous driving or riding behavior minimizing the range of traffic speeds (Kaparias and Wang 2020; Karndacharuk et al. 2014; Tzouras et al. 2022). Already, the study of Akgün-Tanbay et al. (2022) has observed that shared space does not seem as chaotic as was expected.

Focusing on non-moving objects, this study revealed that non-signalized pedestrian crossings were considered less safe compared to the complete absence of "zebra" cross-

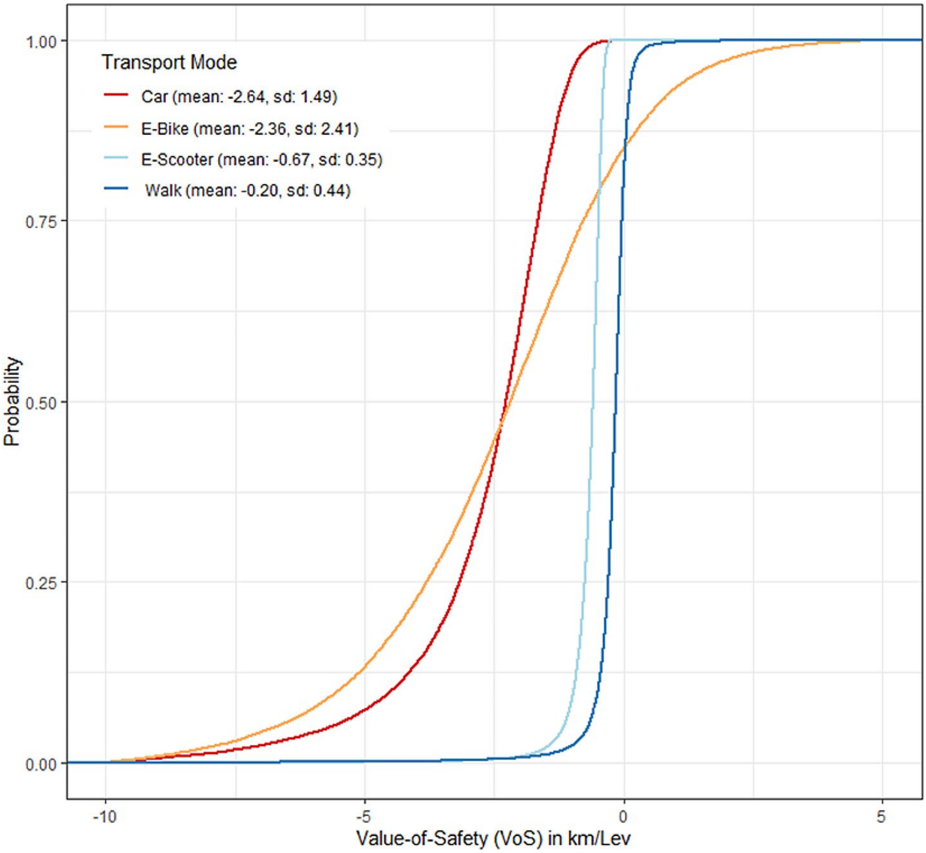

Fig. 6 Cumulative distribution functions of the Value-of -Safety per transport mode – Monte-Carlo simulation (20,000 draws)

ings and road markings, especially for walkers. This is in line with the findings of Gill et al. (2022), but this contradicts the conclusions drawn by Olsson et al. (2023), who found that cyclists perceive roads with clear horizontal signs as safer than those with vertical signs. It should be noted that drivers in Greece are notorious for rarely respecting non-signalized pedestrian crossings, which may be increasing the feeling of unsafety of pedestrians and may be causing some frustration among all road users. The pavement condition and the existence of obstacles are important safety parameters for wheeled modes and pedestrians, respectively. This finding is supported by the study of Nikiforiadis et al. (2023), that have already demonstrated the significance of pavement quality for all road users. Pavements with cracks, potholes, or cobblestone pavements increase the e-scooter vibrations and the unwillingness of using this mode (Calvey et al. 2015; Kaparias and Li 2021; Ma et al. 2021; Sorkou et al. 2022). As for traffic interactions, the perceived safety of car driving was not significantly influenced by the presence of other road users. Unexpectedly, the same was observed in e-scooter riding safety perceptions. The distinction between active and passive users in a mixed-traffic road space, namely, the road user who initiates interactions and the one who merely reacts, appears to be closely related to the study findings. For example, the

Table 5 Mixed logit (ML) mode choice models with random alternative specific constants and beta parameters (all statically significant variables per mode for 95% confidence interval are indicated with * next to the probabilities)

	ML mode choice model											
	Car			E-bike			E-scooter			Walk		
	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)	Est.	Std. E	P(>|z|)
Travel time in minutes	-0.053	0.006	< 0.001*	-0.076	0.013	< 0.001*	-0.078	0.011	< 0.001*	-0.057	0.0038	< 0.001*
Travel cost in euros	-0.424	0.065	< 0.001*	-0.466	0.059	< 0.001*	-0.560	0.077	< 0.001*			
Mean Values												
Alternative specific constant				-0.174	0.428	0.684	-0.688	-0.439	0.117	-0.681	0.401	0.089
Perceived safety in levels	0.450	0.085	< 0.001*	0.844	0.056	< 0.001*	0.763	0.063	< 0.001*	0.440	0.063	< 0.001*
Std. Dev. values												
Alternative specific constant				1.260	0.208	< 0.001*	1.320	0.259	< 0.001*	1.490	0.248	< 0.001*
Perceived safety in levels	0.206	0.097	0.034*	0.228	0.072	0.001*	0.074	0.083	0.372	0.173	0.086	0.044*
Number of observations	1417											
Number of individuals	120											
Null loglikelihood	-982.2											
Loglikelihood at convergence	-811.5											
McFadden's Rho	0.174											
Halton draws	5000											

unpredictable behavior of micro-mobility users (the active users in this case) mentioned in the study of Tuncer et al. (2020) seems to threaten pedestrians, who are perceived as passive users. This is not different of what Gkekas et al. (2020) observed. Pedestrians are more concerned about traffic interactions occurring in non-motorized shared space compared to cyclists. Simultaneously, e-cyclists tend to demand space from car drivers, who are active users in traffic lanes. Indeed, their perceived safety is negatively influenced by traffic density. Scenarios with fewer cars were perceived as safer, as it had also been observed in the study conducted by Olsson et al. (2023).

A challenging part of this approach was related to the connection of perceived safety ratings collected from the first experiment with mode choice responses from the second one. This study proposed a novel methodology to design such a survey. One of the most important outputs of this analysis is the estimation of VoS per transport mode. VoS can give the maximum additional distance a road user is willing to accept so that he/she will travel from a safe first/last mile path by one safety level considering a 7-point Likert scale. Additional distance means increased travel time, cost or both. High VoS results in higher flexibility of the examined mode that is expressed in a relatively more detouring behavior. Of course, it should be noted that this indicator highly depends on the travel speed of each mode. In the estimation of VoS, travel speed was assumed to be constant. Hence, it was expected that private car as a first/last mile transport mode would report the highest value. Unexpectedly, the mean VoS of e-bikes is almost similar to private car. This is because a positive beta parameter of travel time was estimated in the binary regression model of e-bikes. The study of Rossetti and Daziano (2022) have found something really similar. Inexperienced users tend to perceive e-bikes as a mode to have fun, train or relax; yet this perception is not common to all of them. This is also highlighted by the high standard deviation of the VoS parameter in e-bikes, while in e-scooters, there is a very high level of agreement. The low VoS for e-scooters estimated from this experiment reveals that in unsafe road networks, potential travelers prefer to not use an e-scooter than change their paths. E-scooters should not be considered a flexible transport mode to access dense city centers; their flexibility is highly limited by their safety concerns of road users.A plethora of studies have already revealed (Aman et al. 2021; Branion-Calles et al. 2019; Sanders et al. 2020a; Sorkou et al. 2022). The mixed logit model that describes mode choice identified the existence of considerably high dependencies among first/last mile mode choices provided to respondents. Indeed, the standard deviations of the selected random parameters were significant. However, as it was shown, the preference to use a micro-mobility mode can be systematically explained by the perceived safety factor. This happens especially in cities that do not own a dense cycling network (Branion-Calles et al. 2019; Heinen et al. 2010; Livingston et al. 2018; Willis et al. 2015).

The study limitations mostly relate to the sample distribution. This experiment was conducted with participants, who mainly live in Athens, Greece, and do not use micro-mobility modes daily. In this city, access/egress trips from/to metro stations are mainly performed on foot (Kopsidas et al. 2019; Tzamourani et al. 2022), cycling infrastructure is limited, and a large network of pedestrianized zones exists only in selected central areas (Kepaptsoglou et al. 2015). Perceived safety is meaningful as a factor in heterogeneous road environments, in which safety perceptions fluctuate spatially. This mainly appears in micro-mobility modes, while in car driving or walking, perceived safety seems to have a binary format: safe or not safe. This approach was not followed in this study. Moreover, in walking, perceived safety may often be convoluted with other subjective variables, like comfort or security. Both factors can better explain the unobserved disutility of walking than its perceived safety. Road gradient, which is considered in other studies, was not introduced in the experiment. It is a factor more related to the discomfort and perceived safety experienced particularly by the conventional cyclists. Eventually, it can significantly change the path choice causing detouring behavior. Moreover, traffic congestion limits the travel speed, especially of private cars, and therefore it reduces the VoS. This could put micro-mobility modes in a considerably advantageous position, as these can use different parts of the street to keep their speed constant, regardless of car traffic congestion levels. Lastly, only third-person evaluations of perceived safety were collected; therefore, respondents did not experience the traffic situation presented in static images (Gill et al. 2022). Evaluations from field or virtual reality (VR) experiments could further reinforce the validity of the developed models in the future. Last, the selection of independent variables was done based on the study scope and the overall modeling approach. More subjective or objective factors can be integrated in this framework to explore further the challenges of micro-mobility usage.

Conclusions

The effect of perceived safety at the strategic level of the first/last mile travel behavior was modeled in this study by conducting image-based double stated preference modeling and developing ordered and mixed logit models. This study investigated for the first time the following hypothesis: that perceived safety is a significant determinant of first/last mile mode choices and that it differs per transport mode, while a heterogenous urban road environment modifies road users' perceptions downgrading the attractiveness of a transport mode. The scene (i.e., the cross-section), the static and moving objects constitutes the road environment. The study findings support this hypothesis. Especially in the case of e-scooters, it can be concluded that the willingness to use them is severely affected by the low perceived safety reported in most scenarios that were presented to respondents. To move around, a heterogenous road environment with no specialized cycling infrastructure, typical first/last mile transport modes, like private car and walking, are considered safer, especially by females or non-young respondents (over 30 years old).

Based on the results, the segregation of traffic flows raises perceived safety across all first/last mile transport modes, but shared space should be considered as a middle-ground solution. Indeed, shared space was found to reinforce the perceived safety of micro-mobility modes and pedestrians; simultaneously, this design is not as chaotic as it may seem, reporting lower heterogeneity compared to conventional urban road designs. This is also confirmed by the fact that non-signalized "zebra" pedestrian crossings are perceived as less safe compared to not being present at all. In traffic interactions, it can be concluded that e-bikers are threatened by the existence of heavy motorized traffic, while pedestrian safety perceptions are negatively influenced by the intensive use of micro-mobility modes in the same mixed-traffic road environment. Another contribution of this study is the introduction of VoS, which can further describe routing behavior to cover the first/last mile. Considerably low mean VoS was observed in e-scooters, showing the very high unwillingness of respondents to be flexible and detour. They prefer instead to not use this mode at all. On the contrary, the e-bike is a much more promising solution. The mean VoS of e-bikes was found to be almost equal to one of the private car but with a higher standard deviation, which indicates a low level of agreement. Simultaneously, it was noticed that much of the unobserved utility of this mode can be systematically modeled by introducing a perceived safety factor. Therefore, the lack of specialized infrastructure seems to be the only barrier, which should be overcome to increase the cycling demand in Athens, Greece.

Last but not least, this survey was filled mainly by young people who can be considered potential micro-mobility service users. The proposed data collection technique and modeling framework can be applied in different cities also focusing on different social groups. Still, it is reasonable to say that perceived safety is a meaningful factor reflecting the overall accessibility of micro-mobility modes in each urban area or road. It is also a factor to access sustainable urban mobility plans.

Appendix A: Survey Form

Scenario 28

You are here:

Please consider that:

1) In this road, **there is no bike lane**,
2) The **speed limit** is equal to **30 km/h**,
3) There are **wide sidewalks** with width bigger than **2.1 meters**,
4) The condition of the pavement is **bad**,
5) **There are zebra pedestrian crossings** that are **controlled by traffic lights**,
6) On the sidewalk, **there are many obstacles** that may hinder your movement,

How safe would you feed in this road? Rate from 1 (very unsafe) to 7 (very safe).

		1: very unsafe	2	3	4: moderate	5	6	7: very safe
to drive a car	4: moderate							
to ride an e-bike	6							
to ride an e-scooter	4: moderate							
to walk	3							

8. Your daily route consists of urban roads with traffic conditions like above. Which transport mode would you select, if you were aware of the travel time and cost you are going to spend?

- ◯ Car (time: 20 minutes and cost: 5.0 euros)
- ◯ E-bike (time: 5 minutes and cost: 3.0 euros)
- ◯ E-scooter (time: 6 minutes and cost: 0.5 euros)
- ◯ Walk (time: 30 minutes and no cost)

Author contributions PTZ: conceptualization, methodology, data analysis, writing-original draft, project administration. VP: data collection, data analysis, writing-original draft. IK: conceptualization, writing-review and editing. KK: conceptualization, supervision, writing-review and editing. All authors reviewed the manuscript at the end.

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Code availability The estimation codes of the models are available at:
https://github.com/lotentua/Perceived_safety_choices/tree/main/empirical.

Declarations

Competing interests The authors declare no competing interests.

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