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How the design of Complete Streets affects mode choice: Understanding the behavioral responses to the level of traffic stress

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ABSTRACT

Following a federal policy statement in 2010 supporting bicycle and pedestrian accommodation in federal-aid transportation projects, many cities across the US have implemented Complete Streets principles and invested in developing better-planned infrastructure that can be safely accessed by a diversity of modes of transportation by all types of users, in a mix of land uses. However, most of the travel demand forecasting models and planning tools used in practice are not sensitive to changes in demand for non-motorized modes such as walking and cycling in response to road infrastructure improvements. Hence, there is a need for models and tools that are capable of evaluating impacts of infrastructure changes that include Complete Streets implementations on the travel behavior, and estimate shifts in mode choices from motorized to non-motorized modes. This paper proposes a specific data collection plan, a multi-modal choice model, and strategies to update traditional trip-based transportation models to forecast rates of non-motorized trips for evaluating Complete Streets plans at a higher level. Concretely, we estimate elasticities to Level of Traffic Stress, which defines the comfort or discomfort experienced by walkers and bikers, segmented by income levels and trip purposes. We then use them to compute the new non-motorized mode shares that would be achieved by improving CS attributes leading to lower levels of traffic stress. The proposed modeling framework has been successfully applied to the Maryland Statewide Transportation Model, producing reliable non-motorized trip rates, and can be extended to other methodological frameworks used by public agencies.

1. Introduction

The *Complete Streets (CS)* movement, while not called *CS* at the time yet, started in the 1970s as a response to increased automobile dependency in the US after the formation of the National Highway System (Newman and Kenworthy, 1999). The term was first suggested in 2003 by David Goldberg of Smart Growth America at an America Bikes meeting (McCann, 2010). Shortly after the National Complete Streets Coalition was founded (in 2005) and advocated for a Federal Complete Streets legislation in 2008 and 2009, both failed to become law. However, the lack of law was somewhat addressed in 2010 when the U.S. Department of Transportation (US DOT) issued a policy statement on bicycle and pedestrian accommodation, declaring its support for their inclusion in federal-aid

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transportation projects and encouraging community organizations, public transportation agencies, and state and local governments to adopt similar policies. Since then, many cities across the US (and also Canada) have implemented *CS* principles in their transportation plans to guide local transportation agencies on construction and design principles that prioritize pedestrians, cyclists, and transit users.

Concretely, the *CS* concept refers to roads designed to accommodate: (1) diverse modes, including walking, cycling, public transit, automobile; (2) different users, e.g. affluent and low-income individuals, people with disabilities, senior citizens; (3) and a mix of land uses such as office, retail, businesses, and residential, to ensure that streets are safe, balanced and inclusively support diverse economic, cultural and environmental uses (AARP, 2009 & 2015; Burden and Litman, 2011; LaPlante and McCann, 2008; Seskin et al., 2012). It is worth mentioning that since the *CS* concept includes design, urban planning, land use, traffic management principles and other policies that exists in the US such as livable streets (Appleyard 1980), traffic calming (Ewing and Brown 2009) or road diet (Knapp et al. 2014), the term has been used interchangeably with some of them. For the sake clarity, we use the *CS* definition given by the Smart Growth America:

> "*Complete Streets is an approach to planning, designing and building streets that enables safe access for all users, including pedestrians, bicyclists, motorists and transit riders of all ages and abilities. This approach also emphasizes the needs of those who have experienced systemic underinvestment, or those whose needs have not been met through a traditional transportation approach, such as older adults, people living with disabilities, people who don't have access to vehicles, and Black, Native, and Hispanic or Latino/a/x communities*" (Smart Growth America, 2022a).

As such, successful CS projects have prioritized multi-modal transport systems effective in fostering more livable communities, increasing equity and improving public health. Underpinning this model is the intersection of two separate factors: that roads serve diverse functions including mobility, commerce, recreation, and community cohesion; and that road users have multiple mode choice options, including non-motorized modes and well-connected public transit alternatives (Litman, 2015). These infrastructure improvements are expected to ameliorate the quality of life of local communities, enhance the safety of pedestrians and bikers, attract economic investments, promote mixed land use development, reduce emissions, and improve the health of individuals and their well-being (National Complete Streets Coalition, 2021).

Despite the efforts to implement the CS paradigm started decades ago, statistics based on The National Household Travel Survey (2017) (NHTS) show that around 50 percent of all trips made in the U.S. are less than three miles long and that 28 percent of all trips are one mile or less and non-motorized mode share for those trips are 5.7% and 12.7% respectively (NHTS, 2017). These short-distance trips could easily be made by walking, biking, or taking a more environmentally friendly motorized mode such as transit. Yet, the non-motorized modal shares remain very low even for short trips. While the reasons may depend on context and many other factors, one of the major reasons is the fact that the majority of the roads in northern America are designed for automobiles, unpleasant, and unsafe for pedestrians and cyclists, and often infeasible to travel by non-motorized means of transportation (Kuzmyak and Dill, 2012; Cao et al., 2006). In contrast, CS are well-designed, friendlier, and attractive roadways. They have the potential to create opportunities for neighborhood revitalization and attract businesses, jobs, and individuals interested in a less car-dependent lifestyle. These roads can be traveled by various means of transportation, not only by car, inviting people of different socio-demographic characteristics (even elderly or children) to shop locally, commute by transit with improved walk and bike access, play in green areas surrounding the CS corridor, or eat-out in nearby restaurants and coffee shops (Litman, 2015). Additionally, the implementation of CS elements, such as sidewalks, bike lanes separated from the flow of cars, adequate traffic calming measures (speedbumps, roundabouts, median islands, etc.), and smart crosswalk technologies, might reduce fatalities and increase the safety of pedestrians and bikers especially in disadvantaged neighborhoods, where crashes involving pedestrians are much more likely to occur (Ernst and Shoup, 2009).

In light of the benefits offered by the CS paradigm, and the support from the US DOT for inclusion of non-motorized modes in transportation plans, cities and local jurisdictions across the country have been implementing CS transportation plans to guide local transportation agencies on the construction and on the formulation of design principles that prioritize pedestrians, cyclists, and transit users (McCann, 2011). The purpose of these plans is to assess the needs of their communities and the variety of travelers that constitutes them. To this end, they support legislation that prioritizes alternative travel options to the automobile, providing interconnectivity to all modes. However, these efforts are not always accompanied by quantitative studies on the effects of CS on travel patterns, especially those related to the potential modal shift that their implementation may entail. Traditional trip-based transportation demand forecasting models that were initially developed for highway travel in the 1960 s (Button & Hensher, 2005) are still the official planning tools used by many agencies. While significant improvements have been made towards incorporating non-motorized modes in travel demand forecasting in regional models, their representation at the mode-choice model level varies depending on the availability of data and advanced modeling tools such as activity-based models (Singleton et al., 2018). In this context of increasing implementations of CS plans and projects, formal methodologies are needed to adequately incorporate them in existing transportation planning tools where non-motorized modes of walking and bicycling are not part of the mode choice model.

This study aims at filling this gap, offering a guideline to transportation planners and modelers that intend to improve their existing modeling tools to support plans that seek to transform automobile-oriented corridors into CS. This study, based on a research project conducted for the State of Maryland, uses the Maryland Statewide Transportation model to demonstrate the methodology, but the methods proposed are applicable to trip-based four-step travel demand models, and can be easily adopted by any agency or local transport authority, and can be transferred to other geographical areas (Erdogan et al., 2021). The approach that we have developed comprises several steps. First, we collected behavioral data on CS using Stated Preference methods. Second, we model travelers' preferences for non-motorized transportation alternatives in a CS context. In addition to assessing the drivers of the users' behavior, we derive how changes in the characteristics of the CS affect the probabilities of choice of all transportation alternatives considered, (i.e., *direct elasticity* and *cross elasticity*). In this way, we can accurately evaluate how improvements in CS characteristics lead to changes in the demand for all alternatives. Third, we integrate the outcome of model estimation into the Maryland Statewide Transportation Model (MSTM) (Donnelly et al., 2013). In MSTM, the mode choice model does not account for walk and bike modes endogenously, which is the case for many statewide or regional transportation models in the USA. Therefore, we propose to adjust non-motorized trips based on CS plans in the trip generation phase as a percentage of the total number of trips. We then illustrate the proposed approach on an urban region (Baltimore County) visualizing the effects of CS on trips for different purposes and for different income segments.

The remainder of this paper is organized as follows. Section 2 reviews CS literature including case studies and implementations and the effects on modal shift to non-motorized modes. The overall framework is described in Section 3. Data collection effort and the survey design are covered in Section 4 as well as an analysis of the trips reported by the National Household Travel Survey (NHTS), which we used as a baseline for comparison of our results. We describe our approach for modeling behavioral responses to CS in and discuss modelresults and elasticities in Section 5. Section 6 describes our effort to apply the methodology on a transportation model using the Maryland Statewide Transportation Model. Study limitations and future extensions are in Section 7, and policies that support Complete Street projects are highlighted in in Section 8.

2. Literature review

The existing literature on Complete Streets comprises three main aspects; 1) CS policies and projects implementations, as well as their outcomes in mobility and land use (Perk et al., 2015; Moreland-Russell et al., 2013; Burden and Litman, 2011); 2) changes in expected non-motorized trips or modal shifts measured after a CS implementation from available studies or direct observations (Jensen et al., 2017; Yu et al., 2018; Schlossberg et al, 2015); and 3) modeling and planning tools proposed and adopted by agencies to evaluate the effects of CS (Rynne, 2010; Carter et al., 2013). We review these three aspects focusing on U.S. cases, where the problem of incomplete streets is notable and where only recently the attention of legislators and planners has been directed to this issue.

2.1. Complete Streets policies and project implementations

Regarding the first of these aspects, the implementation of policies and projects, as early as 1973, the city of Portland passed a landmark law regulating "U*rban Growth Boundaries (UGB)*," which started several innovative planning projects, including the design of Complete Streets around the city. For many years, the UGB policies were not very successful in controlling urban sprawl or in reducing car use (Jun 2004) and until recently, Portland's streets were not different from those of any other city in the USA (Goldberg, 2018). After 2018, many improvements including e.g. sidewalk expansions, landscaping, green infrastructure for stormwater management such as rainwater collection and filtering have been implemented. Many more people are now walking to their residence and to visit shops and local businesses. Another early example of CS in the U.S., which was not called CS at the time but a boulevard design inspired by multiway boulevards in Europe, is San Francisco's Embarcadero Freeway (Jacobs et al., 2002). This road was demolished after the 1989 earthquake and rebuilt adding a multiway boulevard to a six-lane roadway. It has been reported that after the reconstruction, traffic volumes reduced by 50% and that the number of pedestrians, bicycles, and transit users increased, affecting positively the economy of the nearby neighborhoods (Litman, 2015).

In more recent times, the New York City Department of Transportation updated the *Street Design Manual* in 2009, retrofitting several roadways by adding sidewalks, bike lanes, and bus lanes (New York City, 2020). The 9th Avenue became a CS model under this program, with bicycle lanes separated from traffic by a row of parked cars, signaling for pedestrians and bicycles, and dedicated islands for pedestrians to cross safely. Several benefits have been observed, including reduced congestion, increased transit ridership, higher cycling, and pedestrian activities. Adjacent areas have also been reported to attract more businesses and customers (Litman, 2015). In subsequent years, this plan has been further developed; by 2010 the focus shifted to arterials and their safety; the *Vision Zero* initiative was launched in 2015 to further improve safety; it was followed in 2016 by an action plan to improve public health, expand travel choices, and fight climate change (New York City, 2022). As a result of these efforts, car-dominated arterials had started to be transformed into green boulevards accessible to pedestrians and bikers, that also accommodate bus waiting areas, and where cars travel at a low speed.

Another example in this direction is the Arlington County Board (State of Virginia), which established in 2016 the *Neighborhood Complete Streets* (NCS) program to improve safety and access to local roads; albeit limited in scope since arterials were not part of the plan (Arlington (VA), (2016)). On the other hand, the current Kansas City Region Metropolitan Transportation Plan has developed a CS policy that includes the development of design concepts (Kansas City, 2017). For now, the plan is limited to one major Street and a Boulevard, but the plan also includes training and communication activities together with new guidelines to design bicycle facilities.

In 2020, as part of their CS activities, the City and County of Honolulu reported improvements in pedestrian safety, transit-related enhancement, traffic calming projects, and bike facility installation. In this case, educational efforts were an important part of the effort, too (City of Honolulu, 2014).

The Maryland State Highway Administration (MDOT SHA), encouraged by *PlanMD* legislation enacted in 2012, issued a CS policy that same year. The policy aimed to strengthen the balance between safety and mobility of all roadway users by developing context-sensitive solutions that support the mobility and transit accessibility of pedestrians, bicycles, and individuals with disabilities (Maryland State Highway Administration, 2012). Similarly, in November 2018, Baltimore City Council passed a Complete Streets bill that targeted the improvement of existing legislation and establishing accountability measures for Baltimore City's Department of Transportation (BDOT), to support the city becoming a Complete Streets pioneer (Baltimore City, 2018). However, although these policy efforts are fundamental and necessary, ground truth transit realities in the Baltimore-Washington Metropolitan area are still challenging, both for motorists and even more so for those relying on transit, cycling, and walking.

In conclusion, since the Complete Streets Act passed in 2009, the number of CS policies have significantly increased every year, even doubling in some years. More than half of the states in the country has some form of CS policy at the community or state level (Moreland-Russell et al., 2013). Gregg & Hess (2019) analyzed CS policies by sampling a total of 113 municipal level complete streets policies from The National Complete Streets Coalition's database. They conclude that most of the policies are about street design, but they lack addressing the objective of serving all users of all abilities. As of January 1, 2021, 1,520 jurisdictions in the United States, including 1,312 cities and towns, had adopted some form of CS policy that is intended to support active travel by pedestrians, cyclists, and transit riders by improving the built environment and policy support for walking, cycling, and using transit (Smart Growth America, 2021).

2.2. Modal shifts and non-motorized trip rates

Regarding the second of the aspects mentioned above, the expected changes in the use of transportation modes due to the implementation of CS, although policies aiming at incorporating CS elements into existing networks should be supported by quantitative analyses, the number of studies specifically designed to estimate the effects of CS on modal shares and non-motorized trip rates is rather limited. Local and State planning organizations that work with four-step transportation models often do not include walk and bike alternatives into mode choice model specification (Donnelly et al., 2013, Singleton et al., 2018). Likewise, studies that delve deeper into the travel behavioral changes before and/or after the construction of CS are scarce. In this regard, several studies have focused on the relation between network design and level of bike ridership or pedestrian flows, both usually modeled at aggregated levels.

Concerning bike use, (Dill and Carr, 2003) showed that improved quality, density, and connectivity of the bicycle network favorably affect bike use. Dill et al. (2012) collected Stated Preference data to assess individuals' inclination to bike or walk on different types of facilities (i.e. with or without separate lanes), low or high volumes of cars, slow and fast traffic, the presence of smart technologies that will give priority at traffic signals to pedestrians and bikers. Several researchers have proposed the Level of Traffic Stress (LTS) indicators to describe road conditions and network design (Buehler and Dill, 2016; Cervero et al., 2019; Wang et al., 2020). LTS is measured on an ordinal scale, usually from 1 to 4, with levels at the bottom of the scale corresponding to lower levels of stress. In this vein, Furth et al. (2016), who were among the first to define the LTS in the Netherlands, adopted in their study the following variables to define LTS categories: speed, street width, cycle lane width, speed limit, number of through lanes, and intersection design. Cervero et al., 2019, form their part, used LTS indicators to assess which factors affect cycling to work in 36 urban areas in Great Britain; the study concludes that there is no single factor that boost cycling to work, but "*low stress paths, mixed land use and natural amenities can make a difference*". Wang et al. (2020) adopted LTS criteria to study the relationships between bicycle network design and commute mode shares in Franklin County, Ohio. Their empirical results from aggregated data attest that road segments with a LTS level of 2 are significantly and positively associated with the share of bicycle commuters, while the very low-stress level (LTS 1) are not.

2.3. Modelling and planning tools for Complete Streets

Finally, the number of modeling and planning tools adopted by agencies to effectively design CS and to support their implementation is limited. (Dehghanmongabadi and Hoşkara, 2020) review a broad selection of these frameworks. They identify that these approaches conduct extensive analyses of the social and physical context of the areas where the project is planned by collecting data relative to the present and future characteristics of the zoning, their land use, and the transportation system implemented. Then the authors suggest a policy procedure whereby planners identify the negative and positive aspects of the current network and then propose and test solutions, which are ultimately transferred to engineers who will assess their technical and financial feasibility. On the other hand, Donais et al. (2019) proposed a multi-criteria decision-making framework integrated with a geographic information system to select the streets that should have a higher priority in the context of Quebec City. Jordan et al. (2022) have proposed a new capability maturity model for the evaluation of CS projects that identifies and prioritizes needs, as well as assists in the practice of local agencies. The approach already used in other transportation contexts aims at developing consensus around specific CS projects, identifying and prioritizing needs, and facilitating actions.

Therefore, according to the work described above, it can be concluded that the number of CS projects is increasing in the USA and that planning agencies could benefit greatly from reliable data and evaluation tools to quantify their benefits and to prioritize interventions. It is true that progress has been made in developing indicators that measure the level of stress for walkers and bikers, especially at the network level. However, there is still much to unveil about how travelers behave in the presence of CS; and the state of practice with regard to modeling tools is currently limited in their ability to account for improvements in walk- and bike-ability. For these reasons, we believe that our methodology can make a significant contribution in this regard.

3. Overview of the methodological framework

This section details the methodological framework we followed in this study. Fig. 1 presents an overview of its three major components, namely the stated choice experiment, discrete choice modeling, and application to a transportation model. The Stated Choice Experiment is designed to understand the behavioral responses to changes in level of service, and level of traffic stress by trip distance and by purpose in a CS context (section 4). The information gathered in the survey, as well as interviewees responses to the scenarios, are input in a Discrete Choice model (Multinomial Logit, see section 5) to model individuals' behavior. The outputs of the model are used to compute elasticities and non-motorized mode shares. These were then implemented in a transportation model, the

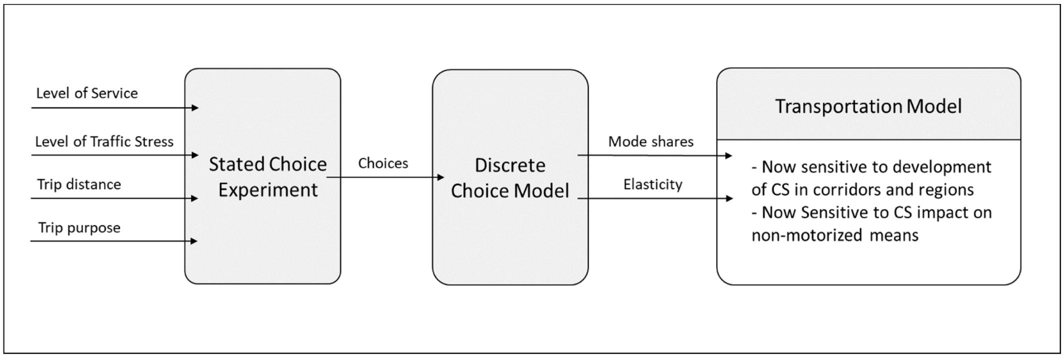


Fig. 1. Overview of the methodological framework.

Maryland Statewide Transportation Model in this study, to evaluate impacts of CS projects on non-motorized mode shares (Section 6).

4. Stated choice experiment

For this specific research question, we designed a Stated Choice Experiment (SCE) with the aim of filling the existing gap in behavioral data relative to the use of CS and to the effects that infrastructure improvements may have on the number of trips made by walking and biking. Specifically, we gathered information on the actual behavior of individuals when they perform short trips, eliciting their preferences towards motorized and non-motorized transportation modes. We did so in a context in which non-motorized means could be hindered by a certain degree of hazardousness in their use. How we treated this specific aspect is fully described in the next section along with the technical aspects concerning the design of the SCE.

4.1. Experimental design

Stated Choice Experiments can be the right tool to collect information on individuals' preferences towards alternatives that do not exist yet, as is the case of CS segments in areas in which they have not been already implemented. The purpose of a SCE is to determine the influence of the characteristics of a set of alternatives on the probability of choosing them. An experiment consists of several hypothetical scenarios in which different levels of the attributes of the alternatives are shown. By evaluating the information presented, the user makes a choice among the available alternatives. In this case, the alternatives presented were *Car, Bike*, and *Walk*, for which we provided information on the attributes *travel time*, *travel cost*, *parking cost*, and *Level of Traffic Stress (LTS)*. LTS is a measure of how difficult —even dangerous— is for bikers and walkers to use the road, and it is described in more detail in the next subsection. It is worth mentioning that, as stated above, we conduct our study on short trips; concretely, shorter than 5 miles. We made this decision for the sake of reality, since we anticipated that only a very reduced number of users would select non-motorized modes for long trips —especially *Walk*, which would have invalidated any trade-off with respect to these modes. Moreover, we defined three different sub-designs based on the length of the trip: *short* (1 mile) trips*, medium* (3 miles) trips and *long* (5 miles) trips. The reason is that although a "short trip" may seem a homogeneous concept, in truth the decision process of a means of transport includes the evaluation of its characteristics, and this evaluation differs when the trip is very short and when it is not so short. For instance, eight minutes of walking may be comparable to four minutes of driving (*ceteris paribus* other aspects of the trip), but 50 min of walking compared to 20 of driving, not so much. The same applies, analogously, to the rest of the trip characteristics considered. By making these sub-designs, in which the values of the attributes shown corresponded to a trip of those characteristics (lower travel times and costs), we offered the interviewee more realistic choice scenarios. It is also worth mentioning that since the choice of a mode may differ significantly depending on the purpose of the trip, the scenarios presented in the SCE referred to one of the following trip purposes: *work, school, shopping, social or recreational*, and *other*. How we treat these aspects is described in the section dedicated to the questionnaire. Finally, we randomly assigned users to these branches (maintaining even shares among them); each of them contained 24 scenarios divided into four blocks, also randomly assigned. In order to produce these choice tasks, we ran the Modified Federov algorithm with 30,000 iterations using the software *Ngene* (ChoiceMetrics, 2014). We opted for an orthogonal rather than an efficient design because of the difficulty of finding in the literature reliable priors. The design was optimized for the estimation of Multinomial Logit and Nested Logit models. Table A1 in the Appendix shows as an example the output of the software for a trip of the type *short* (1 mile).

4.1.1. Attributes, levels, and alternatives

The selection of the attributes to be considered in the survey design was based on a comprehensive literature review related to travel behavior on non-motorized alternatives, as well as on previous research experience and knowledge of the field. As indicated above, four key attributes were retained to define the choice experiment scenarios: *travel time, travel cost (*present only in the *Car* alternative*), parking cost (*present only in the *Car* alternative*), and Level of Traffic Stress* (present only in the *Bike* and W*alk* alternatives). It is worth mentioning that other trip or mode characteristics were considered (pollution, landscape, safety, etc.) but finally discarded.

Table 1
Travel times (minutes) for 1-, 3-, 5-mile trips.

Destination	Length	Actual travel time car	Survey travel time car	Survey travel time bike	Survey travel time walk
Graduate Gardens	1	5	[4,6,8]	4: [4,5,6] 6: [6,8,9] 8: [8,10,12]	4: [8,9,10] 6: [12,14,15] 8: [16,18,20]
Greenbelt	3	9	[10,14,18]	10: [10,13,15] 14: [14,18,21] 18: [18,23,27]	10: [20,23,25] 14: [28,32,35] 18: [36,41,45]
Beltsville	5	12	[13,18,23]	13: [13,17,21] 18: [18,23,27] 23: [23,29,35]	13: [26,30,33] 18: [36,41,45] 23: [45,52,58]

They presented difficulties in their definition as well as cognition by the respondents and could hinder the estimation of the attributes in the choice model, diluting the effect of the main variables of interest, i.e. those related to the CS (LTS).

4.1.1.1. Travel time. Since presenting realistic trips was a priority and given that this study was geographically framed in the State of Maryland, we chose a segment of Route 1 in the City of College Park, as the basis for calculating travel times by car. We explored travel times from this origin (the University of Maryland campus, concretely) to destinations 1, 3 and 5 miles away (see Table 1), under normal traffic conditions. With these references, a time range was determined to be used in the design. Table 1 depicts the actual travel times and the possible combinations of travel times shown in the survey. It can be seen that bike travel times may be, in the best scenario, equal to car travel times, thanks to CS streets elements such as dedicated lanes or safer conditions that make the cyclists ride faster. In the worst case, they are up to 50% longer. Although a car may be more than 50% faster than a bike, again, this hypothetical trip happens in a CS context, in which vehicle traffic calming measures or other elements of the same nature that slow down automobiles are present. Regarding walking times, they at least double car travel times in all cases, and they might be up to 150% longer. Although these specific levels may present scenarios in which the inferred walking speed is particularly high, our aim when defining this range for the walking travel time was to consider that some pedestrians could complete their trips in complete streets by jogging/running and, therefore, achieving higher speeds. Additionally, given that 5 miles is a reasonable distance to walk, and given the willingness of Americans to use their cars, we decided to provide scenarios slightly in favor of walking in order to produce perceptible trade-offs, a common practice in Stated Choice Experiments, where it is important to keep a balance between realistic information and significant trade-offs.

In practical terms, the algorithm performing the statistical design was adjusted to first select a combination of car travel times and then choose the travel times for non-motorized alternatives accordingly, all maximizing the efficiency of the design. In other words, if, for instance, the design had selected a travel time by car of 6 min, the biking travel time would have been selected among 6, 8, and 9 min; while the walking travel time would have been between 12, 14, and 15 min. This avoids a high correlation between the values of these variables.

4.1.1.2. Travel cost. Since we considered maintenance costs negligible for short trips, in this study travel cost only includes fuel cost, calculated as cost per mile[1] times trip miles (and slightly adjusted to stress the differences in the perception of the utility among alternatives). Although we considered to differentiate among types of vehicles –bigger vehicles usually consume more implying higher costs per mile– we finally discarded this possibility because the trips considered were so short that we considered in this case too that such difference would have been negligible. Ultimately, the levels defined for this attribute were $0.5, $1.5, and $2 for short, medium and long trips, respectively. On the other hand, bike and walk travel costs were defined as zero.

4.1.1.3. Parking cost. For the sake of simplicity, and without detriment to the results of this exercise, we decided to simply include fixed parking costs on three levels of variation: $0, $1, and $3, for the three trip types.

4.1.1.4. Level of traffic stress (LTS). Level of Traffic Stress is an indicator, usually expressed on a rating scale, which is intended to provide a measure of how safe and comfortable it is to ride a bicycle or walk on a particular road segment (Furth et al., 2016). Since the State of Maryland's LTS definition and mapping work was still ongoing at the time of this study, we decided to use Bike and Walk LTS levels from 1 to 4 according to a project already implemented, the *Carillion Boulevard Complete Street Corridor Study*[2] (City of Galt, Sacramento). The Bike LTS classification adopted from this study, and used in the survey questionnaire is as follows (Fig. 2 depicts each level):

[1] Fuel costs are based on average prices for the 12 months ending May 31, 2019, as reported by AAA Gas Prices at https://www.GasPrices.AAA.com. During this period, regular grade gasoline averaged $2.679 per gallon.https://exchange.aaa.com/automotive/driving-costs/#.XwRMNudS9hEhttps://exchange.aaa.com/automotive/driving-costs/#.Xw2l2edS-Hthttps://exchange.aaa.com/wp-content/uploads/2019/09/AAA-Your-Driving-Costs-2019.pdf.

[2] A full report of this study can be accessed at https://www.ci.galt.ca.us/home/showpublisheddocument/33864/637296390164470000, while the detailed classification of the LTS levels can be found in its appendix at https://ceqanet.opr.ca.gov/2020031177/2.

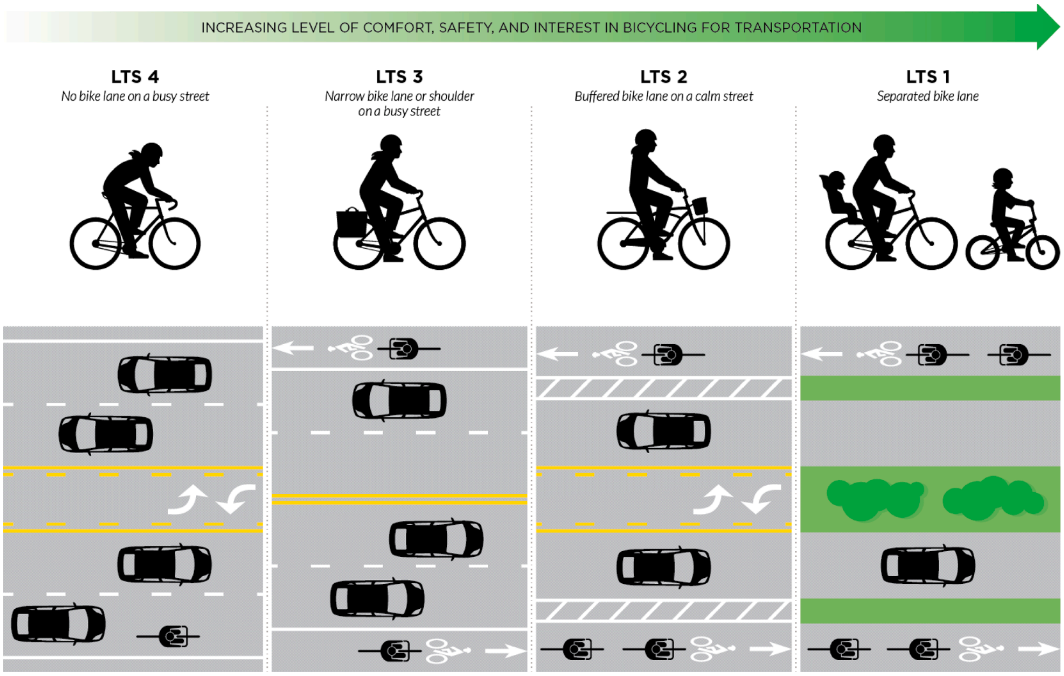


Fig. 2. Level of Traffic stress for bicyclists. Source: City of Galt, *Carillion Boulevard Corridor Plan.*

- **LTS 1**: Represents little traffic stress and requires little attention, so is suitable for all cyclists. This includes children that are trained to safely cross intersections alone and supervising riding parents. Traffic speeds are low and there is no more than one lane in each direction. Intersections are easily crossed by children and adults. Typical locations include residential local streets and separated bike paths/cycle tracks.
- **LTS 2**: Represents little traffic stress but requires more attention than young children would be expected to deal with, so is suitable for teen and adult cyclists with adequate bike handling skills. Traffic speeds are slightly higher, but speed differentials are still low and roadways can be up to three lanes wide for both directions. Intersections are not difficult to cross for most teenagers and adults. Typical locations include collector-level streets with bike lanes or a central business district.
- **LTS 3**: Represents moderate stress and is suitable for most observant adult cyclists. Traffic speeds are moderate but can be on roadways up to five lanes wide in both directions. Intersections are still perceived to be safe by most adults. Typical locations include low-speed arterials with bike lanes or moderate speed non-multilane roadways.
- **LTS 4**: Represents high stress and suitable for experienced and skilled cyclists. Traffic speeds are moderate to high and can be on roadways from two to over five lanes wide for both directions. Intersections can be complex, wide, and or high volume/speed that can be perceived as unsafe by adults and are difficult to cross. Typical locations include high-speed or multilane roadways with narrow or no bike lanes.

Similarly, it was necessary to analyze the effect that better infrastructure for pedestrians has on users' choice to walk. In this regard, the project in the City of Galt that we used as a reference to determine the Bike LTS did not include a similar study for pedestrians and, therefore, we had to turn to another source. In this case, we followed the *2019 Low-Stress Walk and Bike Network Plan* developed by the city of Boulder Colorado[3] which performs the following LTS classification for pedestrians; similar in concept to that described for Bike (see also Fig. 3).

- **LTS1:** Segments and crossings are highly comfortable, pedestrian-friendly, and easily navigable for pedestrians of all ages and abilities, including seniors or school-aged children walking unaccompanied to school.
- **LTS2:** Generally comfortable for many pedestrians, but parents may not feel comfortable with children walking alone. Seniors may have concerns about the walking environment and take more caution. These streets may be part of an otherwise "pedestrian-friendly" environment, intersecting with a more auto-oriented roadway or other environmental constraints.
- **LTS3:** Walking is uncomfortable but possible. Minimal crossing facilities may be present, but barriers are present that make the crossing experience uninviting and uncomfortable. Similarly, sidewalk facilities may be present but inadequate for providing comfort.

[3] The complete plan can be found at https://www-static.bouldercolorado.gov/docs/Low-Stress_Walk_and_Bike_Network_Plan_(modified_4.1.20)-1–202004011307.pdf?_ga=2.129065615.2045802425.1594119846–832671723.1594119846.

Fig. 3. Level of Traffic stress for pedestrians. Source: City of Boulder, *2019 Low-Stress Walk and Bike Network Plan*.

- **LTS4:** Walking is a barrier and is very uncomfortable or even impossible. Crossing and segments have limited or no accommodation for pedestrians.

On the other hand, since users would be choosing among alternatives present in the same road segment, we considered it reasonable to assume that cyclists and pedestrians should experience similar LTS. In other words, a road prepared for cyclists (LTS 1) is also likely to be safe, to some extent, for pedestrians, and vice versa. Following this rationale, we only allowed for a variation of one level, up or down, between the Bike LTS and the Walk LTS. For instance, if Bike LTS was defined as 2 in the design of a scenario, the Walk LTS could only be 1, 2, or 3, but never 4. Finally, we followed a color scheme to inform the respondents of the LTS levels, as shown below in the questionnaire section.

4.1.2. The questionnaire

Although the stated choice experiment was the core of the survey, it was complemented by additional questionnaire modules intended to collect information that could help identify the behavior underlying the choices. Thus, the survey consisted of the following sections:

1. **Last trip.** Information on the last short trip made by the user, including its length, duration, the possibility of having used non-motorized means of transportation to complete the trip, the safety of the road, and the existence of CS elements.
2. **Control questions for experiment logic.** Since mode choice may differ significantly depending on the purpose of the trip, the scenarios presented in the SCE refer to one of the following trip purposes: *work, school, shop, social or recreational*, and *other*. In order to make these scenarios more realistic, we asked the user if she was retired or had any condition that prevented her from working, if she had school-age children, and if she was a student. Depending on the responses, some purposes were discarded from the random assignment made on the SCE –for instance, *work* did not appear if the interviewee was retired.
3. **Information about CS.** Information on CS, including external links and real pictures were presented to the respondent (Fig. 4). In this section we also asked if the information provided was enough for the respondent to understand what a Complete Street is and its purpose. We also directed respondents to sources where they could obtain more information about CS.
4. **Pre-scenarios information.** This section introduced the SCE and gave instructions on how to proceed through it.
5. **Stated Choice Experiment.** As indicated above, the SCE was dynamic. Rules were applied to assign users to the branch of the questionnaire that best matched their characteristics, also taking into account randomness and maintaining a balance in the composition of the sample. Thus, in the first place, when the respondent entered the survey, a trip length (1, 3, or 5 miles) was randomly assigned. Then one of the corresponding four blocks of six scenarios created in the statistical design was mapped to the choice tasks that the person would face. Moreover, these choice tasks did not only include the attributes of the alternatives (travel time, costs, and LTS) and the length, but also the purpose of the trip and if it was home-based or non-home-based. These aspects were randomly generated, too, considering the filters set on point 2 of this list, and. Fig. 5 shows an example of one of these hypothetical situations.

Information about Complete Streets

We now provide you the following public information about *Complete Streets*; what they are and what are their purposes and advantages over regular street designs.

Please take a few minutes to read the materials. If you want to learn more, we invite you to visit the following links and read the information provided by the U.S. Department of Transportation, and the Maryland Department of Transportation

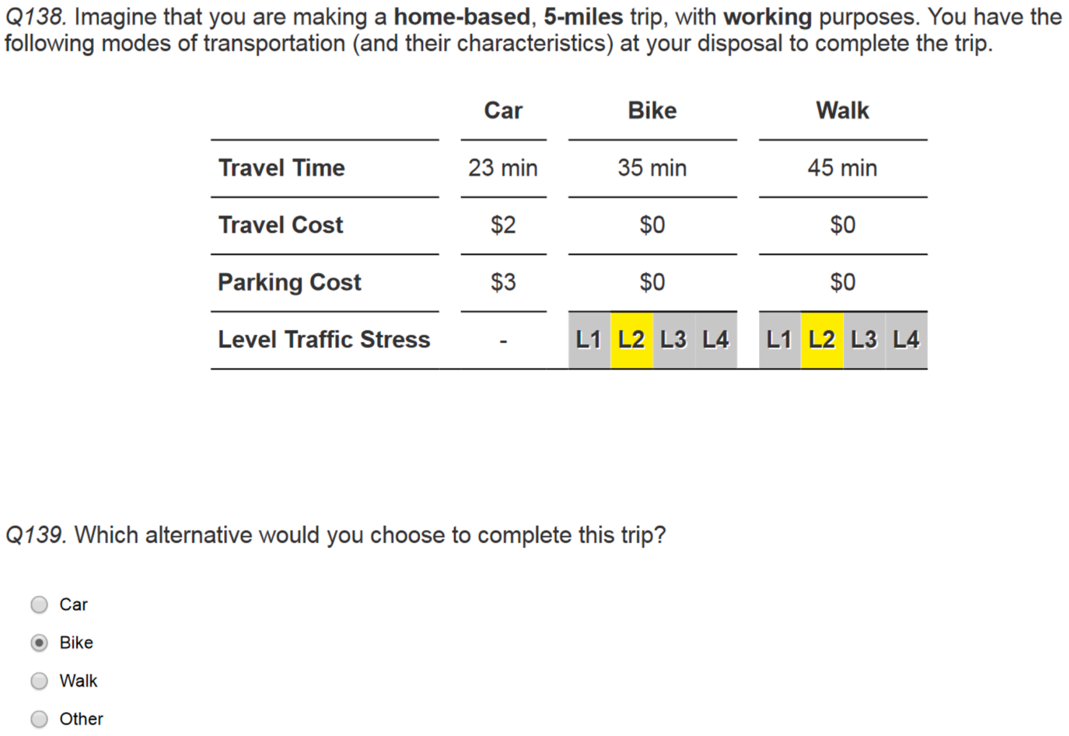
Complete Streets

Complete Streets are streets designed and operated to enable safe use and support mobility for all users, regardless of whether they are travelling as drivers, pedestrians, bicyclists, or public transportation riders. The concept of Complete Streets encompasses many approaches to planning, designing, and operating roadways with all users in mind to make the transportation network safer and more efficient. These designs may address a wide range of elements, such as sidewalks, bicycle lanes, bus lanes, public transportation stops, crossing opportunities, median islands, accessible pedestrian signals, curb extensions, modified vehicle travel lanes, streetscape, and landscape treatments.

The State of Maryland adopted new legislation in 2018 to promote the adoption of Complete Streets policies at the state and local level. The definition of policy and guidelines for underserved and under invested communities is part of the short-term schedule of the Maryland Department of Transportation.

Fig. 4. CS information provided before the SCE.

6. **Attitudes towards Complete Streets.** The first question in this section presented a list of CS elements (such as paved shoulders, wide sidewalks, dedicated bicycle lanes, etc.). We asked the user to indicate how important each of them was for her. The second question presented a list of statements related to environmental concerns and urban design concepts (such as *Urban design should be adapted to non-motorized vehicles*) and asked the respondent to state her level of agreement with that statement.


Q138. Imagine that you are making a **home-based**, **5-miles** trip, with **working** purposes. You have the following modes of transportation (and their characteristics) at your disposal to complete the trip.

	Car	Bike	Walk
Travel Time	23 min	35 min	45 min
Travel Cost	$2	$0	$0
Parking Cost	$3	$0	$0
Level Traffic Stress	-	L1 L2 L3 L4	L1 L2 L3 L4

Q139. Which alternative would you choose to complete this trip?

- Car
- Bike
- Walk
- Other

Fig. 5. Example of a home-based, 5-mile trip for the purpose of work.

7. **Bicycle ownership.** In this module respondents were asked about their bike ownership status and usage.
8. **Ride-hailing usage.** In this module respondents were presented with questions concerning the use of ride hailing services.
9. **Socioeconomic information.** Individual and household socioeconomic information such as age, gender, income, vehicle ownership, etc. were collected.

4.2. *Data analysis*

4.2.1. *The 2017 National Household travel survey*

To check for consistency with the rationale of our survey, and to set a baseline for comparison of our results, we analyzed non-motorized behavioral patterns using real/experienced data extracted from the 2017 National Household Travel Survey add-on data relative to the State of Maryland. We focused our analyses on modal share, modal share by trip purpose, and modal share by trip length. Table 2 shows the main mode chosen by travelers according to NHTS2017 data, overall and by purpose. Namely, the trip purposes considered in NHTS are *Home-Based Work*, *Home-Based Shopping*, *Home-Based Social and Recreational activities*, *Home-Based Other*, and *Non-Home-Based.* The majority of the overall trips are made by Car (86.50%), followed by Walk (8.80%) and Public Transportation (2.98%), while only 0.87% of the trips were made by Bike. Moreover, Walk is the second most used means of travel after the car in all trip purposes except for work trips, in which the use of Public transportation is superior (2.68% vs. 3.64%). On the other hand, the use of bicycle is marginal for all the purposes considered. When we compare these shares with those of our survey (see Table A2 in Appendix), we do not find significant overall divergences in the use of means of transportation, except for the case of the Walk alternative (-4.63 percentage points). By purpose, the largest disparities (superior to nine percentage points) mainly occur in the Car alternative; our interviewees drive more for social and recreational purposes, while less for work and non-home-based purposes. Our sample also

Table 2
Mode shares by trip purpose, NHTS, State of Maryland.

Mode	HBW	HBSHOP	HBSOCREC	HBO	NHB	Overall
Car	92.17%	92.96%	76.77%	80.42%	87.47%	86.50%
Walk	2.68%	4.96%	19.04%	12.11%	7.87%	8.80%
Bicycle	1.04%	0.57%	2.11%	0.91%	0.54%	0.87%
Public transportation	3.64%	1.18%	1.58%	6.12%	2.45%	2.98%
Other	0.47%	0.33%	0.50%	0.44%	1.68%	0.84%

Note: Acronyms used in Table 2 are as follows. Trip purposes HBW: Home-Based Work, HBSHOP: Home-Based Shopping, HBSOCREC: Home-Based Social and Recreational, HBO: Home-Based Other, NHB: None-Home-Based.

seems to walk significantly less for social and recreational purposes as well as for other purposes.

On the other hand, we sought in this study to apply the results of our preferences model to the MSTM. Therefore, we also needed to evaluate the purposes already historically defined in it. We found that these were slightly different than those in NHTS. The list of purposes used in the MSTM included Home-Based School instead of Home-Based Social and Recreational. Also, Non–-Home-Based purposes were split into work and other trips. This difference in classifications led us to define our own list of purposes for the experiment design, which did not exactly match with that of the NHTS or the MSTM, but served better for the modeling work at hand. Namely, we defined the following six trip purposes for our study: Home-Based Work (HBW), Home-Based Shopping (HBSHOP), Home-Based Social and Recreational (HBSOCREC), Home-Based School (HBSCHOOL), Home-Based Other (HBO), and Non-Home-Based (NHB). Our rational for this classification is that an important number of trips are made daily with school purposes, so leaving them out of the analysis like NHTS would not completely represent the behavior of travelers. In contrast, home-basedwe did not split the Non-home-based this purpose into two, as in MSTM, which would not lead to any significant improvement in the model. For the sake of clearity, Table 3 presents the trip purposes of NHTS, MSTM, and our study.

We also analyzed the distribution of trip lengths by mode in NHTS2017 data, as trip length is a significant factor for Complete Streets (Table 4). In this case, certain dichotomies can be observed in the length of the trips made by travelers. Overall, 56.05% of the trips are shorter than 5 miles, while 17.84% are less than one mile. It can be observed that for this very short distance the share between Car and Walk is close (58.64% and 38.27%), while for longer distances individuals clearly prefer to use the car (between 85.70% and 93.43% in trips longer than one mile). The opposite occurs with walking, an option clearly discarded when the trip is longer than one mile. Regarding public transportation, its use is less for very short trips (1.44%), increasing for the longer ones, but never reaching a share higher than 5%. Finally, biking is a means of transportation that is clearly not widespread among users. In summary, the use of the private car is predominant when the length of the trip is longer than one mile.

These findings helped in taking our decision of constraining the study to trips of length 5 miles or shorter. We believed that trips over 5 miles cannot be realistically done by walking, at least in a significant amount. We also restrict bike trips to the same 5-mile threshold, given their very limited modal share in NHTS. Regarding transit mode, we decided not to include it in the survey design. The reasons are twofold. First, the model estimation was conducted to be used within a statewide travel demand model which was splitting trips into two categories: motorized and non-motorized in the generation step. Including public transportation options in the questionnaire would require us to separate motorized mode share into two categories before the mode choice. Second, including transit in the questionnaire would introduce complications in the survey design as the number of options to be provided would increase significantly and it would be confusing and time consuming for the respondents as well. To avoid these complexities we decided to consider only three modes; car, representing motorized modes; and walk and bike, representing non-motorized modes. The comparison against our sample data yields very similar shares, below one percentage point in most cases, except for the use of Car in trips shorter than a mile. In this case, in our sample data that share is 66.67% while it is 58.64% in NHTS.

4.2.2. *Survey data analysis*

The data for this study was collected using Qualtrics services (Qualtrics Research Core) and through a research panel in two phases: a pilot (100 complete surveys collected) and a final launch (766 complete surveys out of 1,756 invites). We imposed three socio-economic variables of control (age, income, and gender) for the sample recruitment and verified that they were met in the final sample. Qualtrics probably gives a monetary incentive to the members of the panel; however, the amount of this incentive and the form used to disburse it by Qualtrics is not known. The pilot was launched with a two-fold aim. First, to check questionnaire consistency. Minor errors were identified during this phase that did not require any significant modification of the structure of the questionnaire or its flow. The second objective of conducting a pilot was the estimation of preliminary models, similar to those that would ultimately be

Table 3
NHTS, MSTMS, and our study.

NHTS	MSTM	Our study
Home-Based Work	Home-Based Work	Home-Based Work
Home-Based Shopping	Home-Based Shopping	Home-Based Shopping
Home-based Social/Recreational	Home-Based School	Home-based Social/Recreational
Home-Based Other	Home-Based Other	Home-Based Other
Non-Home-Based	Non-Home-Based Work	Home-Based School
	Non-Home-Based Other	Non-Home-Based

Table 4
Trip length by mode according to NHTS2017, State of Maryland, data (miles).

Mode	<1	1–2	2–3	3–4	4–5	5+
Car	58.64%	85.70%	91.67%	93.45%	94.39%	93.43%
Walk	38.27%	7.97%	2.78%	2.10%	0.53%	0.22%
Bicycle	1.21%	1.24%	0.67%	0.99%	0.53%	0.25%
Public transportation	1.44%	4.67%	4.50%	3.09%	4.56%	4.93%
Other	0.44%	0.41%	0.38%	0.37%	0.00%	1.17%
Overall (per trip)	**17.84%**	**14.34%**	**10.29%**	**7.97%**	**5.62%**	**43.95%**

Table 5
Average trip length by purpose (NHTS2017, State of Maryland).

Trip Purpose	Min	Pctl.25	Median	Pctl.75	Max	Mean	Std. Dev.
Home-Based Work	1	3	4	5	5	4	1.22
Home-Based Shopping	0.2	2	4	5	5	3.32	1.48
Home-Based Soc & Rec	0.25	2	3	5	5	3.42	1.49
Home-Based School	1	3	5	5	5	3.96	1.43
Home-Based Other	0.2	2	3.6	5	5	3.38	1.48
Non-Home-Based	0.5	2	4	5	5	3.57	1.47

Table 6
Share (percentage) of trip purposes (NHTS2017, State of Maryland).

Trip purpose	Share
Home-Based Work	8.92
Home-Based Shopping	37.31
Home-Based Social and Recreational	17.38
Home-Based School	2.89
Home-Based Other	13.43
Non-Home-based	20.05

calculated. This is a capital step on studies of this nature since any identification problem, non-significant coefficients or, in general, results that deviate from what is reasonably expected, must be addressed before full data collection. Precisely, in our case, we decided to adjust some of the levels of the alternative's travel times, to stress more the differences among alternatives[4]. It was not necessary to modify the LTS levels as they were highly significant from the outset.

After a thorough analysis of the responses, the pilot and launch data were merged, and some observations removed due to inconsistencies, yielding a total of 862 completes (5,172 pseudo-observations). Table A3 in the appendix shows the statistics of the most important variables. The socioeconomic characteristics chosen as control variables (age, gender, and income) for the panel, reasonably match census information for the State of Maryland. The second section of the table refers to trip revealed preferences, i.e., the last trip made by the interviewee. Average travel time was 17.9, while average length was 3.5 miles.

Additionally, users felt that those trips were safe since the mean of this variable is 3.9 over a maximum safety of 5. Interestingly, to the question *Would you say that the road infrastructure allowed for this trip to be made by non-motorized means such as walking or biking?* they declared 3.1, on average, expressed in the same Likert scale (*definitely not - definitely yes*).

Of special interest are the results of the information collected on the importance of several CS elements (6th module of the questionnaire). All of them appear to be reasonably important to users. (means higher than 3), being the most relevant one the existence of wide sidewalks, paved shoulders, medians, and traffic calming measures. On the contrary, bicycle parking, landscaping or truck mountable curbs in roundabouts are the features to which users state that they do not attach much importance.

The variables about attitudes reflect agreement with sentences in favor of both motorized and non-motorized means of transportation, as well as with pro-environmental or pro-ridesharing statements (ATT_EC2 is expressed in negative terms, so disagreement to it means actually environmentally friendly). Finally, the variables about bike ownership show that 50% of the sample own a bike. Among these individuals, many of them use it to get to work (average frequency of 3.6 in a Likert scale), but only to get to another main means of transportation (commute to bus or metro), since 1.5 is the mean value to the use of the bicycle as the main means of transportation to go to work.

We also derived the statistical information from NHTS2017 about the revealed preferences (Table 5 and Table 6), which also served to confirm the assumptions we made for the design.

5. Modeling behavioral responses

5.1. Models for travel behavior assessment

As for the analysis of individual preferences towards non-motorized means of transportation, we estimated a Multinomial Logit (MNL) Model (Ben-Akiva and Lerman, 1985). It is worth mentioning that other models were considered. Namely, we estimated a Nested Logit (NL) structure that grouped non-motorized alternatives, as they might pertain to the same *slow mode* family. However, the tests performed with both pilot and released data showed that there was not significant improvement in the use of NL. Therefore, all analyses and results presented in the following Sections are based on MNL.

The random utility obtained by an individual n when choosing the alternative j pertaining to a set J is:

$$U_{nj} = \beta_n' x_{nj} + \varepsilon_{nj} \quad (1)$$

[4] It is worth mentioning in this regard that Table 2 above presents the final levels appearing in the full launch of the survey, and not those intermediate levels that are mentioned here.

where x_{nj} are observed attributes, $\beta_n^{'}$ is a vector of coefficients representing individuals' tastes, and ε_{nj} is the error term independently and identically Gumbel distributed. Having defined the linear combination of estimated coefficient and alternative attributes as the deterministic part of the utility V_{nj}, the choice probabilities can be expressed as:

$$P_{ni} = \frac{e^{\beta_n^{'} x_{ni}}}{\sum_j e^{\beta_n^{'} x_{nj}}} \tag{2}$$

On the other hand, one of the key elements in this project was the calculation of elasticities. Elasticities represent the change in the probabilities of choosing an alternative in response to a change in some observed factors. For instance, to what extent car would be less demanded if car travel times would increase, or how many more people would choose to walk or bike if safer and better roadways would be available. These are the so-called *direct elasticities*. On the contrary, to what extent the probabilities of choosing an alternative are affected by a change in the attribute of another alternative (to what extent *Bike* would be more demanded if car travel times would increase) are called *cross elasticities.* In the case of discrete choice models, such as the MNL, the calculation of elasticities involves the derivatives of the choice probabilities. Ultimately, they can be calculated (direct and crossed, respectively) as shown in Eqs. (3) and (4):

$$\xi_{iz_{ni}} = \frac{\partial V_{ni}}{\partial z_{ni}} x_{ni} (1 - P_{ni}) \tag{3}$$

$$\xi_{iz_{ni}} = -\frac{\partial V_{ni}}{\partial z_{nj}} x_{ni} P_{nj} \tag{4}$$

If utilities are linear in parameters $\beta_n^{'}$ the derivatives become $\beta_z x_{ni}(1 - P_{ni})$, and $\beta_z x_{ni} P_{nj}$, respectively (Train, 2019).

5.2. Model estimation results

Following the specification defined in the previous section, several models were estimated with a two-fold aim. Our first objective was to identify the key variables that influence users' choice of motorized and non-motorized modes of transportation. These variables included the *Level of Service - LOS* (the attributes defined in Section 4.1.1), socioeconomic factors, and the purpose of the trips treated as dummy variables. However, for the sake of completeness, and related to the second goal of these estimations, we also estimated a series of models only on the data corresponding to each purpose. That is, one model in the subset of data corresponding to the scenarios in which the purpose was *work,* one model in the subset of data corresponding to the scenarios in which the purpose was *shopping*, and so on. Moreover, since we presumed that income could also play a key role in the preference for non-motorized means, we ultimately estimated one independent model on the subsample of each combination of purpose and income bracket (5 purposes, 5 income brackets; 25 in total). The income brackets were defined in accordance with the structure of the MSTM, given our interest in updating the non-motorized trip table generation module of this statewide model.

The second aim of these estimations was to calculate elasticities from the coefficients obtained. Namely, the direct and cross elasticities for each attribute, for each alternative, for each of the 25 models. This led to the estimation of 525 elasticity values. In addition to the intrinsic value of these calculations in understanding the changes in the probability of using each alternative when the characteristics of the CS change, we use the elasticities to compute non-motorized modal shares in the MSTM by updating the non-motorized trip table generation module. However, it is important to highlight that, due to data sparsity, some of these sub-models were not completely identified, or provided results contrary to expectations. In those cases, as will be explained below, we opted for using the elasticity from the general model to carry out this update, since they were highly reliable given the larger amount of data used for their estimation, and its coherence.

Thus, Table 7 below presents the results of the general model (whole sample, purposes as dummy variables), and the specific models estimated on each subset of the data (one for each purpose). For the sake of brevity, the results of the other 25 models are not reported, only the elasticities obtained from them.

With reference to the model estimated on the complete dataset, the attributes referring to the alternatives have the expected negative effect (time, cost, level of stress) and in most cases are also highly significant. Some LOS are not, but they do provide interesting insights concerning travel behavior on Complete Streets. Travel time by bike or walk are highly significant variables, while travel time by car is not. This is a natural result in this specific experiment since driving time for short trips is small and, therefore, increments on it do not make users change their minds. In other words, once driving, even a 100% increase in driving time from 2 to 4 min, is not perceived as a big loss. Something similar occurs with the travel cost by car, which is not perceived as harmful as the parking cost (which can go up to $3). It is especially significant the effect of LTS for both non-motorized modes, as well as their more negative coefficient, emphasizing how important this aspect is when making the decision to walk or use a bicycle. Finally, not all trip purposes played a relevant role in users' choices. Only shopping was the purpose that had a significant effect. Expressed differently, the purpose of the trips is not that relevant when users are deciding among Car, Bike, or Walk in the context of Complete Streets[5]. On the other

[5] It is worth clarifying that we do not state that the purpose of a trip does not influence the choice of a non-motorized means of transportation, but that it is not significant when the trip takes place on a road segment that is a CS.

Table 7
Modeling results.

	General model		Purpose Work		Purpose School		Purpose Shopping		Purpose Social		Purpose Other	
	estimate	t-ratio	estimate	t-ratio	estimate	t-ratio	estimate	t-ratio	estimate	t-ratio	estimate	t-ratio
ASC car	–		–		–		–		–		–	
ASC bike	0.1325	0.63	0.6274	1.56	−0.1374	−0.19	0.0852	0.24	−0.3113	−0.92	0.0174	0.05
ASC walk	0.329	1.35	0.8316	1.71	−0.7198	−0.97	0.4265	0.99	−0.0954	−0.27	0.5523	1.44
ASC other	−3.5578	−14.2***	−2.79	−7.08***	−3.4582	−5.14***	−4.0515	−10.7***	−3.6166	−7.69***	−3.9176	−9.31***
Travel time car	−0.0084	−0.73	0.0066	0.24	−0.0123	−0.29	−0.0305	−1.25	−0.0028	−0.11	−0.0166	−0.63
Travel time bike	−0.0319	−4.01***	−0.0228	−1.42	−0.0412	−1.47	−0.0585	−3.56***	−0.0299	−1.76	−0.0343	−2.03*
Travel time walk	−0.0469	−7.16***	−0.0428	−3.29***	−0.0271	−1.43	−0.0719	−5.77***	−0.0524	−4.22***	−0.0574	−4.77***
Male	0.2495	2.89***	0.3792	2.19*	0.1084	0.4	0.209	1.67	0.1105	0.88	0.4107	3.27***
Age	−0.0133	−4.46***	−0.0167	−2.85***	−0.0033	−0.29	−0.0154	−3.34***	−0.0094	−2.27*	−0.0139	−3.26***
Income	0.2997	3.07***	0.4255	2.36**	0.3155	1.11	0.0041	0.03	0.3626	2.49**	0.4026	2.84***
Bike ownership	1.1971	5.95***	1.1871	3.23***	0.5555	1.11	1.6109	4.96***	1.3723	4.33***	0.9705	3.2***
Frequency use bike other	−0.2041	−3.68***	−0.2634	−2.61***	−0.1601	−1.15	−0.2969	−3.45***	−0.1931	−2.27*	−0.1358	−1.6
Travel cost car	−0.1243	−1.47	−0.0547	−0.23	−0.1747	−0.52	−0.1762	−1.02	−0.1612	−0.9	−0.2089	−1.26
Parking cost car	−0.0696	−3.77***	−0.0425	−0.79	−0.1814	−1.89	−0.0447	−0.99	−0.0962	−2.09*	−0.1197	−2.71***
LTS bike	−0.3096	−8.88***	−0.3812	−5.1***	−0.3204	−2.46**	−0.3379	−4.72***	−0.2389	−3.78***	−0.3969	−6.18***
LTS walk	−0.275	−6.54***	−0.3991	−4.32***	−0.2746	−1.66	−0.2966	−3.29***	−0.1757	−2.17*	−0.3956	−4.75***
Purpose work	0.0638	0.84										
Purpose school	0.1852	1.58										
Purpose shop	0.3468	4.23***										
Purpose social	0.0036	0.06										
Adj.Rho-square (0)	0.2909		0.2388		0.2154		0.3621		0.2757		0.2764	
AIC	10180.69		1872.07		720.08		2345.37		2632.61		2654.33	
BIC	10305.18		1943.89		777.11		2423.22		2710.29		2732.15	

*,**, and ***: Significant at the 95%, 97.5%, and 99% levels, respectively.

Table 8
Direct and cross elasticities resulting from the general model.

	Car	Bike	Walk
Travel time Car	−0.0448	0.0636	0.0504
Travel time Bike	0.1333	−0.3923	0.1259
Travel time Walk	0.1629	0.1931	−0.9901
Travel Cost Car	−0.0712	0.1006	0.0814
Parking Cost Car	−0.0400	0.0537	0.0523
LTS Bike	0.1876	−0.5667	0.2027
LTS Walk	0.0960	0.1072	−0.5696

hand, the models estimated for the five purposes considered show results that are coherent with respect to those of the general one. Only the models for purposes *school* and *shopping* present a lower number of significant variables. Regarding the socioeconomic factors, gender, age, pertaining to the medium income bracket, bike ownership, and frequency of use of the bicycle were found significant (the last two only present in the utility function of the Bike alternative).

For the sake of brevity, and without detriment to the overall results, the elasticities resulting from the general model are shown in Table 8, while in the Appendix are presented the purpose-based elasticities (Table A4) and the elasticities of each of the 25 sub-models that combine purpose and income level (Table A5). These elasticities were used to update the Maryland Statewide Transportation Model. It is worth recalling that, since LOS have an inverse relation with the probabilities of choice (the higher the travel time, cost, or LTS; the less the alternative is demanded), the direct elasticities should have a negative sign. Correspondingly, the cross elasticities should be positive (the higher the travel time, cost, or LTS of an alternative; the more the other alternatives are demanded). Additionally, larger elasticity values mean that a 1% change in the LOS has a more larger impact on the probabilities of these alternatives to be chosen.

As expected, travel times and costs negatively impact the demand of the alternatives (increases in these LOS reduce the probabilities of the alternatives to be chosen), although the effect is stronger for Bike and Walk (-0.3923 and −0.9901, respectively). Interestingly, the latter has almost an *elastic* demand (elasticity above one in absolute value). An elastic demand would have meant that increments in walking travel time would have impacted more than proportionally the probability of that alternative being demanded. On the other hand, the magnitude of the elasticity of the travel and park costs is also in line with that of travel time.

However, more important for our analysis is the second factor with the strongest impact on demand, the LTS, which is actually very similar for both the alternatives in which it is present (-0.5667 and −0.5696). A deterioration in the driving conditions for cyclists or pedestrians importantly reduces the willingness to use this means of transportation. Of course, the opposite is also true: implementing roadway improvement policies that reduce the level of stress to which cyclists and pedestrians are subjected to when completing their trips (such as the construction of more Complete Streets elements) would significantly increase the demand for these modes of transportation.

6. Applying on a transportation model

In this section, we describe how the model outcomes obtained in the modeling phase were integrated into the Maryland Statewide Transportation Model (MSTM) to implement the CS design concept with the aim of performing policy analysis (for details, see Erdogan et al., 2021). For a brief explanation of the current MSTM, it considers 1588 statewide model zones (SMZs) that include areas in the States of Maryland, Washington DC, and Delaware, as well as some areas in the State of Pennsylvania. Concretely, 1178 of these 1588 SMZ are located in the State of Maryland. The MSTM, estimated on a 2007 regional travel survey, is a classical four-step model, but in which the mode choice model does not include the Bike and Walk modes. On the contrary, these non-motorized trip shares are estimated in the trip generation phase, which is segmented according to the six purposes indicated in Table 3, and five income levels. This estimation is performed using aggregated survey information at the zone level, by means of linear regression with the following predictors: household, employment, activity densities, measures of transit and car accessibility to residence, employment, and retail. Once the non-motorized trip shares are estimated, they are subtracted from the total trips, and only the motorized trips are carried on into the subsequent phases.

With respect to our objective of evaluating policies for the promotion of the non-motorized means, the most straightforward method would have been to incorporate those alternatives into the choice sub-model to perform policy analysis attending to the attributes incorporated. However, many agencies certainly do not incorporate a discrete choice model in their methodological framework for project assessment. Moreover, in many cases, they do not have an LTS assigned to their zones either. We, therefore, intended to propose a procedure that can be applied by most of the agencies, using the MSTM as a case study. We start by inferring the current LTS of each zone. Then we use the elasticities to LTS obtained in the travel behavior model described in Section 5 to update the non-motorized share based on hypothetical LTS reached after completing the CS design.

Following this procedure, we first approximated the baseline LTS for all zones covered in MSTM. We do so by scaling the current non-motorized shares, which take a value between 0 and 1, to the LTS range, which, as previously described, is from 1 to 4. For instance, if the non-motorized shares in four different zones were 0, 0.33, 0.5, 0.66, and 1, we assigned LTS values of 4, 3, 2.5, and 1, respectively. This means that zones with higher non-motorized shares were assumed to have lower LTS. We rely for this reasoning on the idea that higher shares may be due to traffic conditions more conducive to this type of transport. Secondly, since elasticities measure the percent change of shares in response to a one percent change in an attribute, once the current LTS values are inferred, they

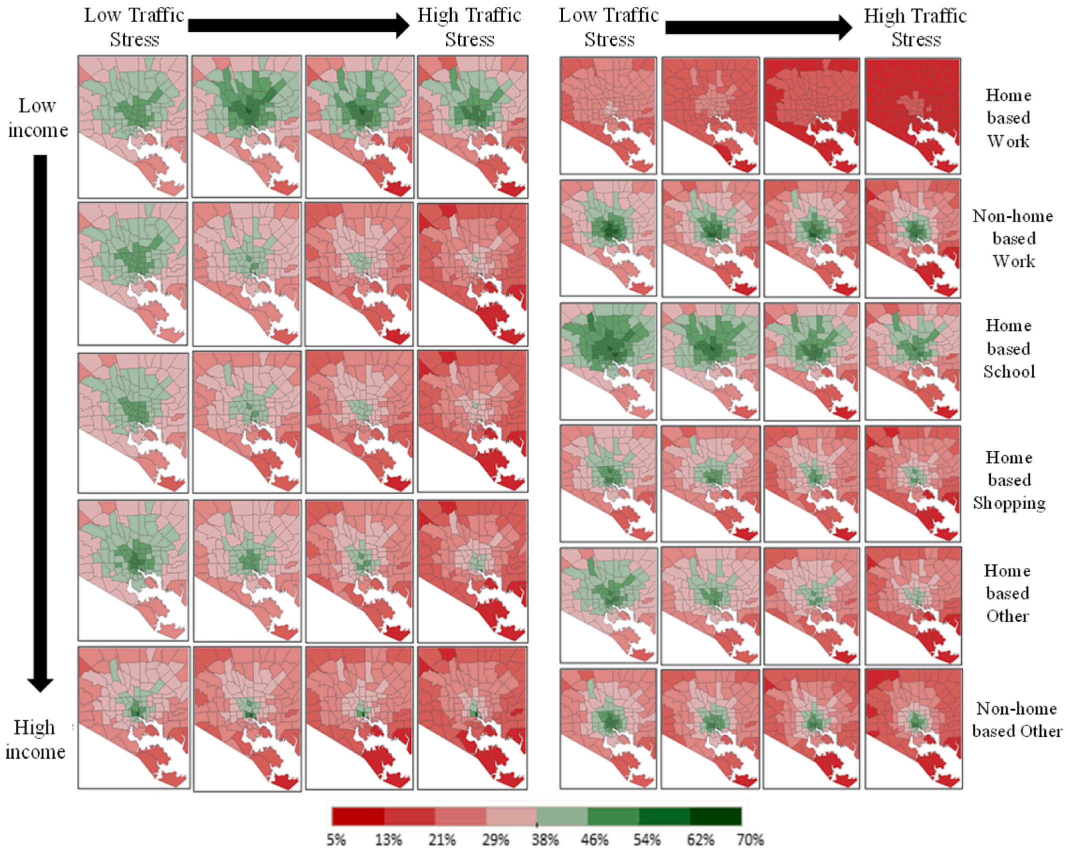


Fig. 6. Non-Motorized mode shares in the Baltimore City by income level (left) and purposes (right).

can be adjusted using the elasticities yielded by the behavioral model[6]. As an example, suppose an area in which motorized share is 88.7% and, therefore, its current LTS is 3.5. How would an improvement in the infrastructure of this area, leading to LTS of 2, impact the use of the available modes of transportation by the lowest income individuals that make trips for working purposes? According to our results, a 1% reduction in the level of stress for bikers and walkers would encourage them, decreasing motorized trips by an average of 0.087% (0.093% and 0.081, first column in Table A5). Thus, following our example, going from a LTS level of 3.5, to a LTS level of 2, which is a 42.9% change, would reduce the use of motorized means by 3.7% (42.9*0.087). The demand for Car would drop from 88.7% to 85.6% and, correspondingly, the demand for non-motorized means would rise from 11.3% up to 14.4%.

An application of this methodology can be found in Fig. 6, from which valuable conclusions can also be drawn on the policies to be implemented for the promotion of non-motorized means. It depicts shares of non-motorized trips for Baltimore City by both income levels (a) and trip purposes (b). A first remarkable result is that the low-income population tends to use more non-motorized modes, although the shares do not seem to significantly increase when LTS improves. This can be seen in the first row on the left side of the figure, where lower LTS levels do not imply a significantly larger green, or even greener, surface on the map. However, this does appear to be the behavior for all other income levels, although very limited in the case of the highest income individuals.

With respect to travel purposes, we can conclude that people hardly walk or bike to work in Baltimore City. Additionally, a large share of trips with educational purposes is made by non-motorized modes, even for high values of LTS. This may be of great interest to the local public authorities since some students might be going to school in unsafe conditions. These routes may be precisely the ones that could benefit the most from a CS redesign. For all other purposes, there is also a general trend that improvements in LTS lead to increased use of non-motorized means in the area, as well as an intensification of their use where they were already adopted.

7. Study limitations and future research

This study has several limitations that have mainly to do with data availability such as the absence of CS projects implemented in the study area, and implications on the methodology. One of them is the absence of real data about existing CS road segments and LTS

[6] We remind the reader that 25 sub-models were calculated, one for each purpose-income combination, and that they can be consulted in Table A5 in the Appendix.

for the road network of the State of Maryland. In order to overcome this difficulty, we had to make assumptions about LTS at the zonal level rather than link level for each zone in the study area based on observed walking and cycling rates. The Maryland Department of Transportation has been working to enhance their transportation model network with the addition of LTS attribute at link level: once that database becomes available, our elasticity estimates can be used for CS corridor projects implementation and evaluation.

The lack of real data also leads to the well-known discussion between revealed and stated preferences. As revealed preferences are, in general, preferable, pre-implementation evaluations for investment decisions that require the estimates of demand for the new CS road segments has to rely on data obtained by stated preferences, i.e. requires the definition of hypothetical situations so that potential users can evaluate them, even if the exact characteristics of the infrastructure were known in advance. Inevitably, stated preferences are necessary for cases where the study alternatives do not yet exist, despite the well-known drawbacks that this methodology suffers from. In fact, this type of information has some advantages over the collection of real data, such as the evaluation of certain scenarios of interest, which do not necessarily occur or exist in reality. For example, the evaluation of a totally safe infrastructure for cyclists and pedestrians that would relegate to a real second place the use of private vehicles. Such hypothetical scenarios are difficult to evaluate in a real data collection context, making the use of stated preferences relevant and vitally important.

Finally, we would like to emphasize the need for considering the emerging new mobility services, in particular micromobility services such as e-scooters and shared bikes/e-bikes, in CS planning and implementation studies. The micromobility services have seen significant growth in ridership in the last decade as a popular mode of transportation for last/first mile trips as well as for short trips where they are available. According to a recent National Association of City Transportation Officials (NACTO) report, trips made by micromobility systems increased by a 60% from 2018 to 2019 (from 84 million to 136 million). These trips were provided by more than 260 services nationwide, including docked and dockless bikeshare and e-scooter systems (NACTO, 2019). This rapid growth in service provision, as well as in popularity, led State DOTs and cities to find efficient ways to manage deployment, monitoring usage and trends, and identify needs for facility and design improvements to accommodate them. There have been significant efforts in supporting these relatively new options as an alternative to driving for short distance trips and for active travel both on the government and service provider sides (Price et al., 2021). For example, one of the leading micromobility companies, Lime, recently joined the National Complete Streets to support efforts and advocate for investments in facilities such as protected bike lanes, sidewalks, and green spaces. They also conducted ridership analysis on new bike lanes and slow streets in London, Berlin, Paris, and San Francisco, providing evidence for increase in ridership on such facilities from Lime riders alone. In San Francisco, Lime ridership increased 28% on the new "Slow Streets'' from November 2019 to November 2020, while increase went up to 111% in Europe (Smart Growth America, 2022b). Therefore, we believe that further research that would build upon the study presented in this paper may also benefit from the inclusion of micromobility systems, as more data becomes available.

8. Supporting Complete Streets policies

The case study explored in this work supports Maryland State Highway Administration's Complete Streets vision with reliable data and models that could be integrated into their planning process using existing tools. However, this vision is shared by many other planning agencies across the USA who are seeking to *plan, design, build, maintain, and operate* (https://minneapolis2040.com/policies/complete-streets/) a more sustainable, accessible, and equitable transportation system. Therefore, we consider that the analysis conducted, and the results obtained may form the basis for the following action steps, addressed to public agencies and transport authorities.

First, the existing modeling tools (and methodological frameworks, in general) discussed in section 2 seem to lack a methodology for analyzing the specific effect that CS plans may have on non-motorized market shares. Therefore, we suggest adopting the easy-to-implement, highly-descriptive methodology presented in this work, which would provide a quantification of the changes in the demand of motorized and non-motorized means of transportation when CS elements are implemented in urban designs. It can be used even when a mode choice (Walk, Bicycle) is not part of an initial transportation model or even when the model does not explicitly account for non-motorized modes at all. Hence, we believe that it can certainly assist planning agencies in their task of assessing this type of projects, as has been the case with the Maryland State Highway Administration.

However, for an evaluation tool to be comprehensive, it must consider elements as well beyond travelers' behavior change, equity being one of the most relevant. In this regard, our results show that the low-income population is more likely to use non-motorized modes (especially walking) and that they walk out of necessity even when the level of traffic stress is high. This conclusion is in line with earlier studies that have shown that low-income communities are disproportionately affected by unsafe streets and limited access to jobs and opportunities (Ernst and Shoup, 2009). Therefore, we suggest to transportation authorities the implementation of Complete Streets with adequate traffic calming measures such as reduced speed limits, and change road design to improve safety using e.g. smart crosswalk technologies, curb extension, raising crosswalks, or adding midblock crosswalk, sidewalk, and bike lanes where there are none. Especially in disadvantaged neighborhoods, to reduce fatalities and increase the safety of pedestrians and bikers. In this vein, our results for Baltimore city have also shown that a relatively high percentage of trips to school are non-motorized and that they happen in unsafe conditions. Therefore, we suggest prioritizing projects around schools, especially in an urban context, by creating pedestrian/biking priority networks and by improving connectivity across neighborhoods.

It is worth noting, as indicated in the numerical example given in Section 7, that improvements in LTS may not lead to substantial impacts on the use of non-motorized modes for certain trips and user characteristics. That is, even in a scenario that is entirely favorable to pedestrians and bicyclists, individuals may simply not want to walk or bike, or may prefer to use a motorized vehicle due to other personal circumstances or preferences. To be fair, this is one of the limitations of our methodology. We lumped all possible CS elements into only one measure, level of stress/risk. Probably, the explicit inclusion of specific CS elements (such as separated lanes, roundabouts, speed control, etc.) would lead to more accurate elasticities, which ultimately would provide a more comprehensive perspective of the drivers of individuals' preferences towards non-motorized means of transportation. In this sense, it would also be necessary to evaluate different standards along with those proposed in this paper, and to monitor the achievements by comparing them with initial objectives and best practices around the world.

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CRediT authorship contribution statement

Javier Bas: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Mohammad B. Al-Khasawneh:** Conceptualization, Data curation, Formal analysis, Methodology, Software. **Sevgi Erdoğan:** Conceptualization, Investigation, Funding acquisition, Project administration, Supervision, Writing – review & editing. **Cinzia Cirillo:** Conceptualization, Investigation, Funding acquisition, Project administration, Supervision, Writing – original draft.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

See (Tables A1-A5).

Table A1
Orthogonal Design.

Choice situation	Car travel time	Car travel cost	Car parking cost	Bike travel time	Bike LTS	Walk travel time	Walk LTS	Block
1	4	0.5	1	6	1	9	2	3
2	4	0.5	3	5	2	8	1	1
3	4	0.5	0	4	1	10	1	4
4	4	0.5	1	6	3	10	2	2
5	6	0.5	1	6	4	14	4	2
6	6	0.5	0	6	1	12	1	4
7	8	0.5	0	10	4	20	3	4
8	8	0.5	3	12	3	20	3	2
9	6	0.5	1	9	1	14	2	1
10	8	0.5	1	12	4	18	4	3
11	8	0.5	3	8	1	18	1	2
12	8	0.5	3	10	2	18	1	3
13	6	0.5	0	9	3	12	2	3
14	8	0.5	0	8	2	20	2	1
15	8	0.5	3	12	2	16	2	4
16	4	0.5	3	5	3	10	3	1
17	4	0.5	1	5	4	9	3	3
18	6	0.5	0	9	1	15	2	1
19	4	0.5	3	4	3	8	4	3
20	6	0.5	0	8	4	12	4	1
21	6	0.5	3	6	3	15	4	4
22	4	0.5	1	6	2	8	3	4
23	4	0.5	1	4	4	9	3	2
24	8	0.5	0	10	2	16	3	2

Table A2
Comparison of percentages of transport mode use by purpose between sample data and NHTS, State of Maryland. Difference expressed in percentage points (Sample minus NHTS percentage).

Mode	HBW	HBSHOP	HBSOCREC	HBO	NHB	Overall
Car	−6.46	−0.72	9.90	8.94	−5.97	1.56
Walk	1.22	−1.23	−12.37	−9.98	−3.25	−4.63
Bicycle	2.86	0.05	−0.11	−0.91	1.19	0.40
Public transportation	2.85	2.24	3.09	1.68	6.22	2.70
Other	−0.47	−0.33	−0.50	0.27	1.79	−0.03

Table A3
Descriptive statistics of the main variables in the dataset.

Variable	Mean/Mode/Share	Std. dev.	Min.	25%	Median	75%	Max.
Sociodemographics							
Age (numeric)	42.3	17.5	18	27	40	58	87
Gender (dummy)	41.3%	0.5	1	1	2	2	3
Married (dummy)	45.4.5	0.5	0	0	1	1	1
Employment Status (categories)	1	–	1	1	3	7	9
Education level (categories)	4	–	1	3	3	4	5
Household income (numeric)	75,202.1	239,441.7	0	40,004.5	38,000	100,000	1,000,000
Interviewee only worker in household (dummy)	0.9%	0.5	0	0	1	1	1
Individual income (numeric)	32,070.3	56,805.3	0	18,400	3,000	50,000	600,000
Retired or condition preventing from working (dummy)	0.3%	0.4	0	0	1	1	1
School-age children in household (dummy)	0.3%	0.4	0	0	1	1	1
Student (dummy)	0.2	0.4	0	1	1	1	1
Last Trip							
Trip length, minutes (numeric)	17.9	50.0	1	5	10	15	1,000
Number of miles (numeric)	3.5	1.5	0	2	4	5	5
Home-based (dummy)	1.2	0.4	0	0	0	0	1
Trip safety perception (Likert)	4	1.1	1	3	4	5	5
Trip could be made by non-motorized means (Likert)	3	1.3	1	2	3	4	5
Number of trips working day (numeric)	2.8	1.4	1	2	2	3	7
Number of trips weekend (numeric)	3.0	1.4	1	2	3	4	7
Importance Complete Streets elements							
Paved shoulders (Likert)	4	1.1	1	3	4	4	5
Wide sidewalks (Likert)	4	1.1	1	3	4	4	5
Dedicated bicycle lanes (Likert)	4	1.2	1	3	4	4	5
Dedicated bus lanes (Likert)	4	1.3	1	2	3	4	5
Pedestrian medians (Likert)	4	1.1	1	3	4	4	5
Traffic calming measures (Likert)	4	1.1	1	3	4	4	5
Mountable curbs (Likert)	3	1.2	1	2	3	4	5
Bus stop access (Likert)	4	1.2	1	3	4	4	5
Bus stop shelters (Likert)	4	1.3	1	3	4	4	5
On-street parking (Likert)	3	1.2	1	2	3	4	5
Bicycle parking (Likert)	3	1.3	1	2	3	4	5
Landscaping (Likert)	3	1.2	1	2	3	4	5
Attitudes							
Attitude towards cars #1 (Likert)	4	1.1	1	3	4	5	5
Attitude towards cars #2 (Likert)	4	1.1	1	3	4	5	5
Attitude towards cars #3 (Likert)	3	1.2	1	2	3	4	5
Attitude non-motorized means #1 (Likert)	4	1.0	1	3	4	4	5
Attitude non-motorized means #2 (Likert)	4	1.0	1	3	4	5	5
Attitude towards shared means (Likert)	4	1.2	1	3	4	4	5
Attitude environment #1 (Likert)	4	1.1	1	3	4	4	5
Attitudes environment #2 (Likert)	3	1.3	1	2	3	4	5
Bike use							
Bike owner (dummy)	51%	0.5	0	0	0	1	1
Frequency biking working purposes (Likert, decreasing order)	5	1.4	1	3	4	5	5
Frequency biking other purposes (Likert, decreasing order)	3	1.1	1	2	3	4	5
Bike as main mean for working (dummy)	25%	0.5	0	0	0	1	1
Bike as main men for other purposes (dummy)	23%	0.5	0	0	0	1	1

Table A4
Direct and cross elasticities resulting from the purpose sub-models.

	Home-Based Work			Home-Based School			Home-Based Shopping			Home-Based Social			Home-Based Other		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	0.0351	−0.0410	−0.0329	−0.0679	0.0830	0.0812	−0.1190	0.2392	0.1856	−0.0142	0.0190	0.0149	−0.0827	0.1056	0.0826
Travel time Bike	0.0951	−0.2393	0.0891	0.1657	−0.4632	0.1700	0.1759	−0.6925	0.1747	0.1229	−0.3335	0.1139	0.1326	−0.3700	0.1291
Travel time Walk	0.1440	0.1671	−0.8137	0.1077	0.1123	−0.6325	0.1702	0.2158	−1.3965	0.1721	0.2034	−1.0056	0.2005	0.2469	−1.0524
Travel Cost Car	−0.0306	0.0356	0.0290	−0.1042	0.1274	0.1257	−0.0736	0.1475	0.1178	−0.0880	0.1170	0.0941	−0.1122	0.1426	0.1138
Parking Cost Car	−0.0248	0.0276	0.0266	−0.0958	0.1162	0.1205	−0.0189	0.0356	0.0360	−0.0511	0.0644	0.0620	−0.0659	0.0780	0.0773
LTS Bike	0.2391	−0.6201	0.2536	0.1933	−0.5401	0.2004	0.1457	−0.5853	0.1694	0.1400	−0.3939	0.1545	0.2245	−0.6382	0.2376
LTS Walk	0.1317	0.1458	−0.7311	0.0938	0.0933	−0.5406	0.0730	0.0866	−0.5839	0.0591	0.0669	−0.3384	0.1418	0.1555	−0.7112

Table A5
Elasticities resulting from the 25 sub-models that combine purpose and income level.

	Income Bracket 1 Home-Based Work			Income Bracket 1 Home-Based School			Income Bracket 1 Home-Based Shopping			Income Bracket 1 Home-Based Social			Income Bracket 1 Home-Based Other		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	−0.079	0.103	0.078	0.126	−0.152	−0.163	−0.284	0.532	0.367	0.073	−0.109	−0.099	−0.026	0.039	0.037
Travel time Bike	0.201	−0.572	0.186	0.200	−0.651	0.247	0.196	−0.709	0.180	0.117	−0.445	0.116	−0.549	0.160	0.195
Travel time Walk	0.151	0.182	−1.208	0.044	0.051	−0.333	0.179	0.234	−1.702	0.123	0.136	−0.686	−0.841	0.120	0.153
Travel Cost Car	−0.055	0.072	0.055	−0.331	0.402	0.424	0.021	−0.039	−0.028	−0.042	0.062	0.057	−0.135	0.202	0.190
Parking Cost Car	−0.057	0.071	0.072	−0.099	0.127	0.129	0.116	−0.066	0.116	−0.029	0.043	0.041	−0.066	0.097	0.099
LTS Bike	0.093	−0.271	0.103	0.233	−0.731	0.247	0.079	−0.292	0.094	−0.005	0.021	−0.007	0.211	−0.723	0.259
LTS Walk	0.081	0.100	−0.647	0.160	0.177	−1.198	0.034	0.041	−0.309	−0.065	−0.082	0.374	0.105	0.125	−0.717
	Income Bracket 2 Home-Based Work			**Income Bracket 2 Home-Based School**			**Income Bracket 2 Home-Based Shopping**			**Income Bracket 2 Home-Based Social**			**Income Bracket 2 Home-Based Other**		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	0.266	−0.282	−0.257	−0.363	0.421	0.420	−0.157	0.270	0.251	−0.197	0.263	0.194	−0.135	0.172	0.111
Travel time Bike	0.025	−0.064	0.024	0.222	−0.560	0.254	0.244	−0.944	0.265	0.106	−0.260	0.088	0.147	−0.374	0.110
Travel time Walk	−0.341	0.081	0.086	0.139	0.156	−0.988	0.208	0.240	−1.253	0.217	0.241	−1.227	0.320	0.368	−1.426
Travel Cost Car	−0.025	0.026	0.024	−0.078	0.090	0.092	−0.124	0.212	0.200	−0.079	0.104	0.079	−0.307	0.387	0.257
Parking Cost Car	−0.011	0.011	0.011	−0.152	0.174	0.189	0.024	−0.040	−0.042	−0.046	0.056	0.056	−0.067	0.074	0.071
LTS Bike	0.262	−0.699	0.276	0.139	−0.988	0.156	0.168	−0.657	0.196	0.276	−0.696	0.265	0.320	−1.426	0.368
LTS Walk	0.163	0.173	−0.688	0.108	0.101	−0.712	0.105	0.121	−0.631	0.093	0.085	−0.489	0.179	0.170	−0.743
	Income Bracket 3 Home-Based Work			**Income Bracket 3 Home-Based School**			**Income Bracket 3 Home-Based Shopping**			**Income Bracket 3 Home-Based Social**			**Income Bracket 3 Home-Based Other**		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	0.390	−0.365	−0.288	−0.056	0.088	0.059	0.120	−0.325	−0.230	−0.200	0.219	0.151	−0.827	0.735	0.627
Travel time Bike	−0.299	0.510	−0.306	0.278	−0.910	0.294	0.096	−0.450	0.128	0.482	−0.946	0.492	0.421	−0.936	0.418
Travel time Walk	0.018	0.023	−0.115	0.307	0.454	−1.803	0.112	0.217	−1.447	0.246	0.358	−1.749	0.354	0.401	−1.486
Travel Cost Car	0.270	−0.251	−0.201	−0.337	0.517	0.377	−0.109	0.293	0.212	−0.065	0.071	0.051	0.523	−0.472	−0.405
Parking Cost Car	0.047	−0.041	−0.041	−0.272	0.402	0.319	0.005	−0.013	−0.013	−0.012	0.012	0.011	−0.014	0.012	0.012
LTS Bike	0.400	−0.724	0.485	0.078	−0.269	0.106	0.228	−1.093	0.343	0.201	−0.407	0.242	0.291	−0.682	0.350
LTS Walk	0.145	0.170	−0.881	0.017	0.023	−0.095	0.110	0.175	−1.341	0.160	0.254	−1.185	0.147	0.176	−0.626
	Income Bracket 4 Home-Based Work			**Income Bracket 4 Home-Based School**			**Income Bracket 4 Home-Based Shopping**			**Income Bracket 4 Home-Based Social**			**Income Bracket 4 Home-Based Other**		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	−0.240	0.379	0.272	−0.848	0.751	0.892	0.653	−2.453	−1.423	0.345	−0.373	−0.287	1.448	−1.537	−1.776
Travel time Bike	0.215	−0.733	0.259	0.411	−0.997	0.499	−0.246	1.435	−0.222	−0.089	0.203	−0.108	−0.706	1.824	−0.914
Travel time Walk	0.272	0.468	−2.178	0.213	0.217	−0.841	0.123	0.199	−1.495	0.099	0.147	−0.570	−0.706	−0.914	1.824
Travel Cost Car	−0.413	0.643	0.497	0.812	−0.740	−0.854	−0.623	2.216	1.407	−0.522	0.553	0.441	−0.100	0.103	0.121
Parking Cost Car	−0.049	0.068	0.073	0.087	−0.082	−0.087	0.069	−0.217	−0.215	−0.124	0.126	0.115	−0.139	0.138	0.160
LTS Bike	0.372	−1.302	0.508	0.213	−0.841	0.217	0.236	−1.470	0.312	0.429	−0.955	0.460	0.364	−0.974	0.475
LTS Walk	0.164	0.212	−1.168	−0.021	−0.026	0.089	−0.035	−0.043	0.400	0.258	0.295	−1.331	0.127	0.117	−0.606
	Income Bracket 5 Home-Based Work			**Income Bracket 5 Home-Based School**			**Income Bracket 5 Home-Based Shopping**			**Income Bracket 5 Home-Based Social**			**Income Bracket 5 Home-Based Other**		
	Car	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**	**Car**	**Bike**	**Walk**
Travel time Car	−4.754	6.044	2.818	NA	NA	NA	NA	NA	NA	−1.183	1.041	1.037	0.138	−0.205	−0.130
Travel time Bike	−0.143	0.844	−0.464	NA	NA	NA	NA	NA	NA	1.229	−1.936	1.749	0.285	−0.846	0.222
Travel time Walk	0.019	0.122	−0.175	NA	NA	NA	NA	NA	NA	0.361	0.525	−3.344	0.339	0.430	−1.418
Travel Cost Car	4.212	−5.970	−2.897	NA	NA	NA	NA	NA	NA	−0.252	0.227	0.211	−0.535	0.760	0.531
Parking Cost Car	−0.342	0.319	0.300	NA	NA	NA	NA	NA	NA	−0.185	0.162	0.174	−0.086	0.104	0.107
LTS Bike	0.009	−0.071	0.046	NA	NA	NA	NA	NA	NA	0.149	−0.223	0.185	−0.413	1.321	−0.454
LTS Walk	0.045	0.199	−0.329	NA	NA	NA	NA	NA	NA	0.203	0.343	−2.035	−0.075	−0.119	0.339

Appendix A. Supplementary material

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tra.2023.103698.

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