Modeling spatial and social interdependency effects on commuting mode choice

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ABSTRACT

In daily life, individuals are influenced by the behaviors of others. The question of how far-reaching this social influence extends to travel behaviors has received significant attention in recent decades, through the capture of dyadic interaction effects that may exist among individuals. Along these lines, in the current study, we apply a Spatial-Attitudinal Probit Model (SAPM) that assumes an autoregressive lag structure in the utilities underlying individuals' travel mode choice, specifically focusing on the choice between car and public transportation for commuting trips. Notably, the magnitude of interdependency among decision agents is measured by a global weight matrix, accounting for a dual source of influence: (1) spatial proximity, measured as the Euclidean distance between individuals' residential locations, and (2) attitudinal similarities, specifically perceptions regarding sustainable mobility and environmental awareness. To our knowledge, this represents the first application of an autoregressive travel mode choice model accounting for both geographical and attitudinal proximity as simultaneous sources of interaction. The dataset for our analysis includes 2,347 observations, corresponding to the one-way commute trips of 2,347 individuals, as reported during a survey conducted between October 2019 and January 2020 in the metropolitan area of Cagliari, Italy. Our results reveal the significant role of social autoregressive parameters and the presence of interdependency effects among individuals' commute mode choices. The utilization of a social lag structure allows for the separate identification of direct and indirect effects of explanatory variables. Notably, around 40% of the total effect is attributed to the indirect effects arising from individuals' social interdependencies. This finding holds important implications for evaluating and planning potential future measures aimed at increasing public transit usage.

Keywords

Social influence; Mode choice; Spatial model; Interdependency effect

1. INTRODUCTION

People are social beings, inherently inclined to interact and influence each other's behaviors in everyday lives (Páez and Scott, 2007). Individuals also consciously or subconsciously adapt their choices and actions to align with prevailing social norms or the behaviors of those around them. This inclination is evident in a wide range of situations, from fashion trends and dietary preferences (Cruwys *et al*., 2015; Loureiro *et al.*, 2017) to political activism/mobilization and career choices (Bond *et al.*, 2012; Eesley and Wang, 2017). Social psychologists ascribe such individual adaptation behavior (or socially influenced behavior) as an attempt to invest minimal amounts of cognitive energy when making time-tested (in their respective social spheres) informed decisions (informative motivation) and/or as a response to the social peer pressure of being accepted as a member of their social group (normative motivation). The first motivation may particularly arise in completely new or emergency situations (Páez and Scott, 2007), while the second is characterized by the willingness to preserve social acceptance, prevent feelings of loneliness, and develop group identity (Abou-Zeid *et al*., 2013).

The question that arises, and to which this study aims to contribute, is the extent to which socially influenced behavior (regardless of the informative or normative motivation pathways) affects travel choices. Specifically, this study focuses on the impact of social influence on the decision-making process that leads to the choice of transportation modes, and the subsequent implications for the adoption of sustainable travel habits. In the past two decades, there has been a growing emphasis on studying the impact of such social influence in shaping mobility and activity-travel behaviors. For example, some earlier studies have examined the effect of perceived social pressure on travel-related decision-making using revealed preference surveys through an investigation of the observed choice behavior of an individual within the context of the social reference group of that individual (see Bamberg *et al.*, 2007, and Belgiawan *et al.*, 2017). In other studies, researchers have focused on assessing the impact of social influence through stated preference surveys in which various uptake levels, such as the percentage of colleagues or friends making a certain transportation choice (see Cherchi, 2017, and Kim and Rasouli, 2022), have been tested to investigate the effect of descriptive social norms on the willingness to embrace new forms of mobility. Positive social influence results on travel behaviors have been observed in many of these earlier revealed and stated preference studies, such as in the adoption of Mobility as a Service solutions (see, for example, Kim and Rasouli, 2022), the purchase of electric vehicles (see, for example, Kim *et al.*, 2014, Cherchi 2017, and Saleem, *et al*., 2021), public transportation usage (see, for example, Bamberg *et* al., 2007, Murray *et al*., 2010, and Zhang *et al*., 2016), and carpooling intentions (see, for example, Bachmann *et al*., 2018).

The aforementioned earlier studies on capturing social influence have primarily been based on the notion that individuals in close spatial proximity are influenced by one another (on the basis that close spatial proximity engenders more face-to-face interactions). To capture such spatial proximity effects in the discrete choice decision process, researchers have typically specified the utility that an individual attributes to a specific alternative as being not only a function of that individual's characteristics, but also being influenced by the utilities ascribed by other individuals in close spatial proximity (see, for example, Manski, 1993, LeSage and Pace, 2009, Bhat, 2015, and Bhat *et al*., 2016). Such models are classified under the general label of "spatial econometric models". However, in today's society, where face-to-face interactions are routinely supplemented by (and even sometimes almost completely supplanted by) online social media platforms, the strength of interactions between individuals can be influenced by factors that extend beyond spatial proximity. In particular, another significant source of interaction in choices and behaviors likely arises from the similarity in attitudinal space (Alves, 2018). As suggested by Vinayak *et al*. (2018), individuals sharing similar ideas and lifestyle preferences tend to interact more frequently with each other in virtual space too (the so-called "Echo chamber" effect; see Cinelli *et al*., 2021). In this regard, there is much to uncover about how people are socially influenced through interaction with individuals who share similar attitudes (Vinayak *et al*., 2018). An important contribution of this study is the incorporation of a dual source of social influence (spatial and attitudinal) on the choice of transportation mode, recognizing that social influence can also permeate through attitudinal likeness facilitated by virtual space interactions (and that are not always pegged solely to physical space interactions). Such dual source social influence recognition can not only improve the accuracy and behavioral realism of mode choice models, but also increase the effectiveness of measures and interventions aimed at encouraging a transition from car usage to more sustainable transportation options. This is due to what Bhat (2015) refers to as the "Ripple wave" effect; that is, "*a stimulus applied to one decision agent can get magnified through the agent's interactions with other agents, so that the aggregate-level effect of a policy can be higher than the sum of individual-level effects*". Important also to note is that the use of a dual source of social interaction opens up the possibility of having counteracting effects of influence. For instance, the interdependency between two individuals who are spatially close to each other may be mitigated by their distance in the attitudinal space. In contrast, the influence of an individual in close physical proximity might be amplified if there is similarity in the attitudinal sphere.

The rest of the paper is structured as follows: Section 2 presents a literature synthesis of relevant prior studies and positions the current paper within this larger literature. Section 3 offers a description of the dataset utilized in the model application, while Section 4 outlines the framework of the model. The results of the model estimation are detailed in Section 5, followed by a discussion of potential policy implications emerging from this study in Section 6. Finally, Section 7 concludes the paper by summarizing findings and identifying future research directions.

2. RELEVANT BACKGROUND

Many research studies in the past couple of decades have considered elements of social interactions in mobility and travel behaviors. Some early examples attempted to "create" the social influence network of an individual and then investigate how travel behaviors are influenced within the social network so developed. The creation of the social network itself was based either on an approach to measure the intensity of actual observed social interactions of an individual over a period of time (sometimes referred to as the egocentric approach; see, for example, Kowald *et al.*, 2009) or an approach that was based on simulating a social network by pre-specifying the intensity of interactions among synthetic agents (sometimes referred to as the agent-based simulation approach; see, for example, Páez and Scott, 2007). Unlike these studies that are based on a priori explicit social network formation (and that do not always explicitly consider spatial proximity considerations in social network formation), our synthesis of the literature will be focused on studies that are based on implicit or endogenous social network formation by specifying functional forms to represent the intensity of social connections and then estimating the intensity of such connections.

Traditionally, the effect of interdependency among decision-makers on travel behaviors has been modeled using the Brock and Durlauf (2001) (or BD) framework. In this approach, the effect of social influence is measured by incorporating a "field-effect" or "network-effect" as an additional explanatory variable determined by the "average" behavior exhibited by a pre-specified reference group for the individual (such as the share of people in the reference group that use each modal alternative). This BD framework is similar to the egocentric or agent-based simulation approaches that first develop an explicit social network, except that the reference group (that proxies the social network of the individual) in the BD framework is assumed arbitrarily by the analyst (About-Zeid *et al.*, 2013). The basic assumption of studies that implement this BD framework in the context of mode choice models (see Dugundji and Walker, 2005, Göetzke, 2008, and Walker *et al.*, 2011) is that the more a transportation mode is used within the reference group, the more desirable it becomes. In addition to the arbitrary constitution of the reference group (which, however, can be formed based on spatial proximity or attitudinal proximity or a combination of the two), this approach also assumes that the interaction effects are confined strictly within discrete clusters, with equally weighted influence from individuals within the reference group and no influence from those outside the group (Bhat, 2015).

To overcome these limitations, Bhat (2015) introduced a new general endogenous network formation-based methodological approach that involves a single influence network capable of generating varying degrees of social intensity among individuals, while also considering self-selection effects in social network formation and accommodating unobserved heterogeneity in the effects of exogenous variables (with the extent of unobserved heterogeneity itself being spatially dependent in what Bhat refers to as a spatial drift effect). The practical effectiveness of this general methodological framework, even if only in its restricted versions, has been demonstrated through various empirical studies of travel mode choice (see Sidharthan *et al*., 2011, Wang *et al*., 2015, and Mondal and Bhat, 2022). Of particular relevance to the present study is the research conducted by Vinayak *et al*. (2018). They applied a specific version of the methodological approach proposed by Bhat (2015) to investigate the service usage of emerging shared mobility options (ridesourcing/car-sharing services) over the period of a month. Importantly, they enhanced Bhat's approach by employing an autoregressive lag structure that accounts for both spatial (or geographic) and attitudinal proximity. Building on Vinayak *et al*.'s work, our study analyzes the influence of spatial and attitudinal proximity specifically on how utilities of individuals for specific travel modes get impacted in the process of choosing the transportation mode for commuting trips. Different from Vinayak *et al*. (2018) who adopt an ordered-response structure to examine interactions among individuals in investigating the ordinal frequency of using shared mobility options over the course of a month, our study is applicable to the modeling of nominal (unordered-response) outcomes (such as transportation mode choice, with each mode having its own unique attributes, such as travel time and travel cost). To our knowledge, this is the first formulation of a dual source (spatial and attitudinal) spatial-social interaction effect for an unordered-response outcome.

3. DATA DESCRIPTION

The dataset employed in this study originates from a travel survey conducted between October 2019 and January 2020 in the metropolitan area of Cagliari, Italy. Participants, primarily consisting of college students and Public Administration employees, were requested to provide the coordinates for the starting and ending points of their regular commute trip. They also were asked about their usual travel mode choice, including details about its level of service attributes, and the availability of other modes. Additionally, participants were asked to provide information about their individual and household socioeconomic characteristics and respond to a series of questions on attitudinal indicators (*i.e.*, perceptions regarding sustainable mobility and environmental awareness). Furthermore, Geographic Information System (GIS) tools were employed to gather data on the accessibility of public transport and population density within a 500-meter radius around the origins and destinations of the trips.

This study specifically focuses on trips that had a destination within the metropolitan city of Cagliari (excluding destinations in the adjoining rural areas) and that were made by public transport or a private car (in this regard, the application context of our unordered response formulation to a binary mode choice model is equivalent to the application of the ordered-response framework of Vinayak *et al*., 2018, though our formulation can be applied to any number of alternatives within a nominal (unordered) outcome, while Vinayak *et al*.'s framework would not be appropriate to nominal outcomes with more than two alternatives). For each individual, the level of service characteristics of the transportation mode not selected for the commute trip, such as route, distance, and travel times, were obtained using the Google Maps Directions API. For individuals who did not choose public transport for their commute, the corresponding cost of public transport was estimated by identifying the most convenient fare option (single ticket, monthly, or annual subscription) based on their annual trip frequency. On the other hand, for individuals who did not use a car for their commute, the cost associated with using a car was determined by multiplying the distance of the trip by the average cost per kilometer set at 0.17 €/km, which takes into account the cost of the fuel and insurance of a typical compact car in Italy at the time of the interview.[1] In this study, the analysis was limited to participants who had access to both commute modes (in Cagliari, the only public transportation mode is bus, and so we will use the labels "public transport" and "bus" interchangeably in this paper). Moreover, the study only considered trips shorter than 20 kilometers. This condition was set to allow us to focus on urban commute trips and limit the number of outlier observations (see Section 3.2). The final sample used for analysis consists of 2,347 valid observations, corresponding to one-way morning commute trips (either to the physical workplace or to the university).

3.1. Sample characteristics

The characteristics of the sample are summarized in Table 1. The descriptive statistics indicate that slightly more than half of the sample opted for a private car as their mode of transportation to reach their workplace or university. The data also reveals a slightly higher representation of women compared to men and a significantly high proportion of individuals aged 30 years old or younger (every individual is at least 18 years old). The demographic bias towards younger individuals is likely due to the survey's significant focus on college students during its distribution, as also evident from the high portion of students (39.1%) in the sample. This substantial representation of students also

[1] We selected a compact car as the reference car body model because the specific make/model that transit users could have used is unknown. Furthermore, the compact car body model represented the most prevalent body model among individuals in the sample who used a car.

explains the high percentage (30.0%) of individuals reporting a monthly personal income of less than €500. Furthermore, approximately three-quarters of the participants did not have children in their households.

Table 1 Sample characteristics

Variables	**N**	**%**	**Avg.**	**St. Dev.**
Total	2,347	100.0		
Revealed mode choice				
Public transport (bus)	1,076	45.8		
Private car	1,271	54.2		
Gender				
Male	1,005	42.8		
Female	1,342	57.2		
Age	2,347		37.44	14.44
18 - 30 years old	1,008	42.9		
31 - 40 years old	321	13.7		
41 - 60 years old	875	37.3		
over 60 years old	143	6.1		
Student/Work status				
Student	917	39.1		
Workers	1,430	60.9		
Household composition				
No children	1,679	71.5		
At least one child	668	28.5		
Formal educational level				
At least a bachelor's degree	1,144	48.7		
High school degree or lower	1,203	51.3		
Personal monthly income				
under 500 €	704	30.0		
500 - 1,500 €	770	32.8		
over 1,500 €	873	37.2		
Number of cars per adult in the household	2,347		0.76	0.39

3.2. Spatial distribution of observations

The first source of social influence, corresponding to spatial proximity, is derived from the geographic distance among the residences of individuals. Figure 1 plots the spatial distribution of the trip origins (residences) corresponding to the 2,347 individuals in the sample, categorized by the revealed mode choice of the trip. Notably, residential locations are concentrated in urban areas, aligning with the general population density distribution of the area. The majority of the commute trips originate in the city of Cagliari, which serves also as the main destination of the commute trips analyzed in the present study. The decision to include only observations with a travel distance below 20 km was made to narrow the focus of the analysis to urban commute trips.

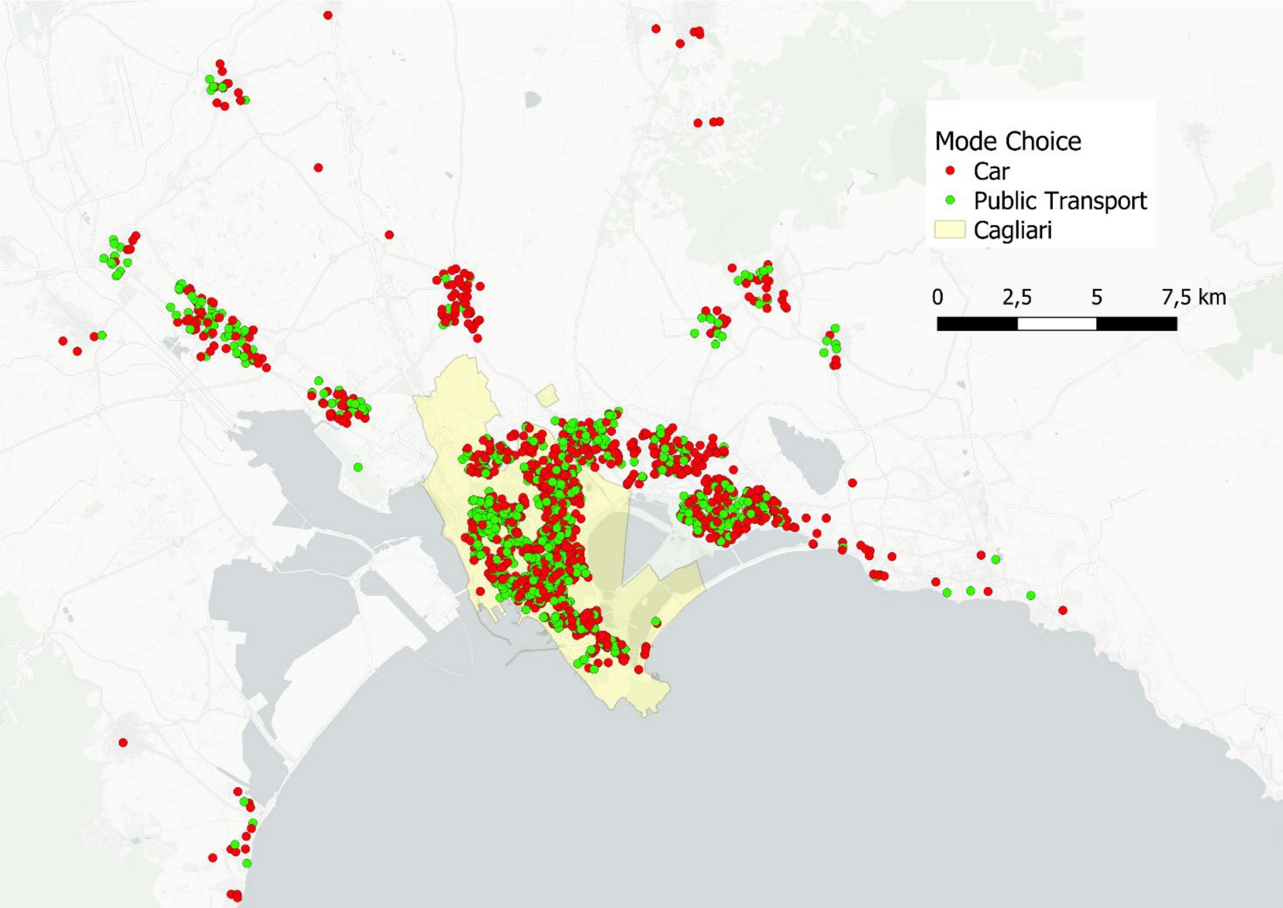

Figure 1 Spatial distribution of trip origins

3.3. Attitudinal measurements

The second source of social influence examined in this study, referred to as the attitudinal influence, relates to the proximity of individuals in the attitudinal space. Individuals who share similar attitudes and preferences are expected to interact more frequently with each other. The study considered the following two latent constructs: perceptions regarding sustainable mobility and environmental awareness. The first attitudinal construct measures how individuals perceive the use of sustainable transportation modes (relative to car use), as measured based on responses to statements associated with sustainable transportation use in terms of utility value, pleasantness, and moral appropriateness (adapted from Carrus *et al.*, 2008). The second attitudinal construct focuses more broadly on general environmental awareness, as developed based on the level of agreement on statements associated with awareness of the environmental and personal health impacts of car usage, as well as their perceived responsibility for the negative impacts of their mode choices (adapted from

Bamberg and Schmidt, 2003). Table 2 shows the statements provided to the 2,347 participants and the distribution of their responses.

A Confirmatory Factor Analysis (CFA) was employed to confirm that the two latent constructs were effectively represented by the listed indicators. Additionally, Cronbach's alpha was employed to assess the reliability of the factors. The outcomes of both the CFA and Cronbach's alphas are detailed in Appendix A.

Table 2 Response distribution to the attitudinal measurements

Latent Construct	Measurement Items	Avg.	Strongly Disagree	Somewhat Disagree	Neutral	Somewhat Agree	Strongly Agree
z_1 Perceptions regarding sustainable mobility	ATT1: I find that using sustainable means of transport instead of the private car is useful.	4.13	3.7%	5.6%	10.2%	35.2%	45.3%
	ATT2: I find that using sustainable means of transport instead of the private car is pleasant.	3.46	9.4%	13.5%	22.5%	31.3%	23.4%
	ATT3: I find that using sustainable means of transport instead of the private car is right.	4.22	1.4%	2.6%	14.1%	36.1%	45.7%
z_2 Environmental awareness	ENV1: I am aware that the use of private car has negative impacts on the environment and people's health.	4.43	0.8%	1.8%	5.2%	38.0%	54.1%
	ENV2: I am aware that I can personally contribute (by using the car less) to reducing pollution.	4.38	1.1%	2.4%	7.3%	36.2%	53.0%
	ENV3: I feel personally responsible for the environmental problems resulting from the choice of my means of transport.	3.51	8.0%	11.5%	20.7%	41.6%	18.3%

The sample revealed an overall agreement with the perception that using sustainable modes of transportation instead of cars is useful (ATT1 in Table 2) and right (ATT3 in Table 2), reflecting a widespread awareness of the positive impacts that reducing car usage can have on society. However, opinions significantly varied regarding the pleasantness (ATT2 in Table 2) derived from using sustainable mobility options compared to car travel. This discrepancy may be attributed to the perceived low quality of public transport in the Cagliari Metropolitan Area, which may be explained by the scarcity of bus-reserved lanes, coupled with a low level of spatial and functional integration among different public transit providers.

Regarding environmental awareness, participants demonstrated a strong consensus on the adverse effects of car usage on the environment (ENV1 in Table 1) and awareness that their own reduced car use can help reduce pollution (ENV2 in Table 2), showcasing a robust consciousness of the negative externalities associated with cars in urban settings. Despite this awareness, a significant portion of the sample acknowledged a low sense of personal responsibility for their mode choices (ENV3 in Table 2). This phenomenon may be linked to social dilemma issues (Van Lange *et al.*, 2013), where individuals recognize the negative consequences of car usage but may not believe that their individual choices can make a substantial impact.

4. METHODOLOGY

The methodology employed in this study is adapted from the works of Bhat (2015) and Vinayak *et al.* (2018). Notably, the use of a dual source of social influence, namely the spatial proximity across peer individuals and their similarity in the attitudinal space (Vinayak *et al.*, 2018), is adapted to the case of a nominal dependent variable with any number of alternatives. In the specific application of our methodological framework in this study, we focus on the binary travel mode choice between private car and public transport.

As shown in Figure 2, the social model framework comprises a two-step analysis (in this paper, we use the term social model to refer to any model that considers interactions among individuals in decision-making; the traditional spatial model considers social interactions arising only from spatial proximity, while our proposed spatial-attitudinal model considers social interactions arising from both spatial and attitudinal proximity). In the first step (see top panel of Figure 2), a structural equations model (SEM) is applied to derive the latent construct values for each individual in the sample. These values are then used to construct an attitudinal weight matrix that is employed in the second step Spatial-Attitudinal Probit Model (SAPM, see bottom panel of Figure 2). Here, the attitudinal weight matrix is combined with the standard spatial weight matrix, which is based on geographical proximity, to formulate a composite spatial-attitudinal exogenous weight matrix $\mathbf{W}$ that is then utilized through an autoregressive lag structure in the utility of alternatives to accommodate spatial/attitudinal interactions among decision agents.

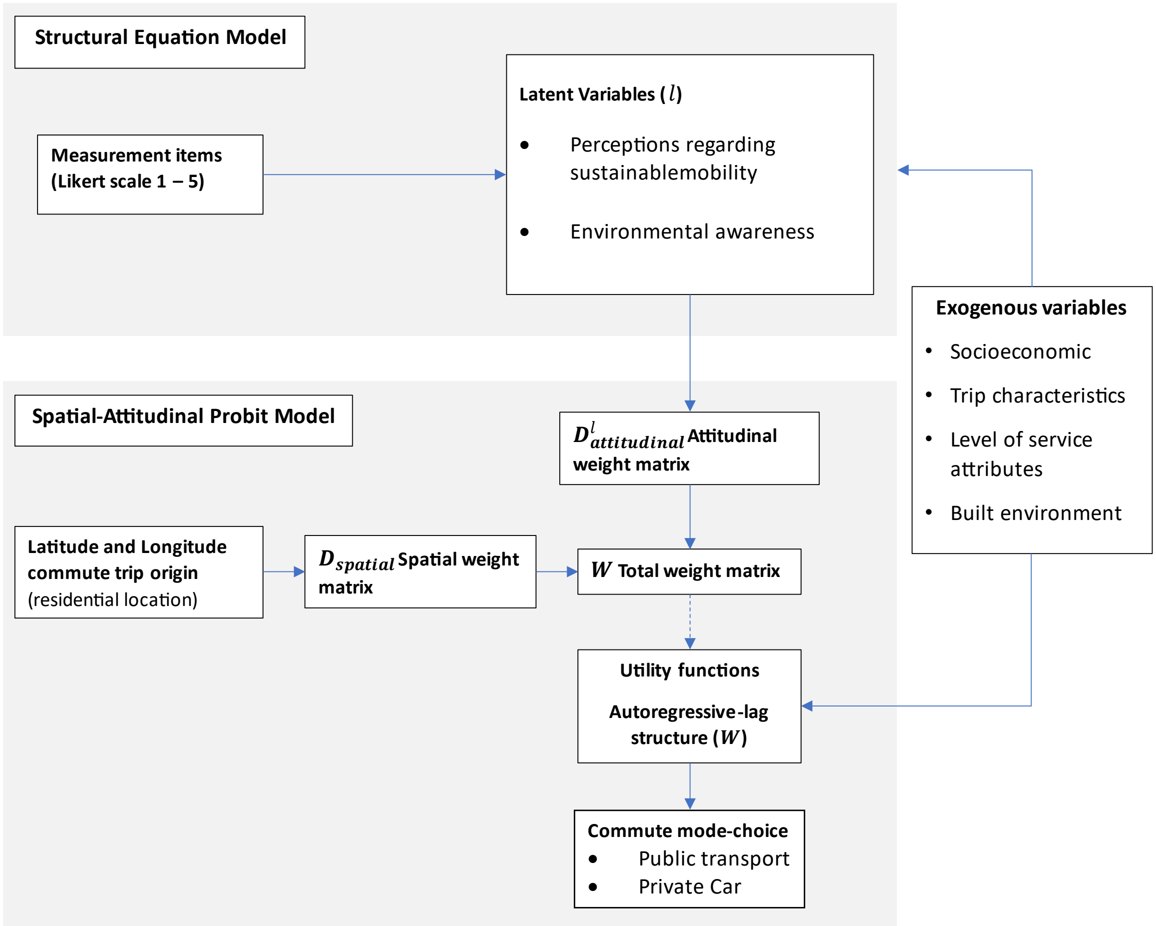

Figure 2 Social Probit Model framework

4.1. Structural Equation Model (SEM)

The initial step involves specifying and estimating an SEM model to derive the expected values of latent variables (z_1 corresponding to perceptions regarding sustainable mobility and z_2 corresponding to environmental awareness) for each individual in the sample. As is standard in such analyses, the SEM comprises two components: the measurement and the structural components. Specifically, the measurement component assesses the extent to which observed measurement items reflect the latent constructs z_{ql} (we introduce the notation *q (1, …, Q)* to denote the index associated with individuals). The index *l (1, …, L; L*=2 in this study) is the index for latent constructs. The structural component relates the latent constructs to exogenous individual characteristics.

Starting with the measurement component, let r_l *(1, 2, …, R; R*=3 in this study) represent the index associated with each of the indicators I_{qr_l} described in Section 3.3 and let *k (1, 2, …,K; K*=5 in this paper) be the index for the ordered frequency categories of each indicator. Each of the indicators is linked to the latent variables through an ordered measurement equation. Thus, the latent propensity $I_{qr_l}{}^{*}$ associated with the r^{th} indicator of the l^{th} latent construct, following the typical framework of ordered probit models, can be written as:

$$I_{qr}{}^{*} = \xi_r z_{ql} + \upsilon_{qr},\ I_{qr_l} = k \ \text{ if } \ \psi_{r_l,k\text{-}1} < I_{qr_l}{}^{*} < \psi_{r_l,k},\ \psi_{r_l,0} = -\infty,\ \psi_{r_l,K} = +\infty, \tag{1}$$

where, ξ_r is the loading of the latent variable z_{ql} and υ_{qr} is a standard normal error term. The ψ_{r_l} terms are the thresholds partitioning the latent propensity $I_{qr_l}{}^{*}$ in K ordinal categories of each indicator of each latent construct.

In the structural component of the SEM, the impact of the observed explanatory covariates on the latent constructs is evaluated. Specifically, the latent variables z_{ql} introduced in equation (1) are specified as a linear function of a set of explanatory socioeconomic characteristics as follows:

$$z_{ql} = \boldsymbol{\lambda}_l \boldsymbol{SE}_q + \omega_{ql}, \tag{2}$$

where $\boldsymbol{\lambda}_l$ is a $(D \times 1)$ estimated vector of coefficients corresponding to a vector $\boldsymbol{SE}_q$ of D observed exogenous variables for each individual q. ω_{ql} is another standard normal error term. In matrix form, we can write Equation (2) as:

$$\boldsymbol{Z} = \boldsymbol{\lambda}'\boldsymbol{SE} + \boldsymbol{\omega},\ \boldsymbol{\omega} \sim MVN_L(\mathbf{0}_L, \boldsymbol{\Sigma}), \tag{3}$$

where $\boldsymbol{Z}$ is an $(L \times 1)$ column vector of the outcomes of the continuous latent variables, $\boldsymbol{\lambda}$ is $(D \times 1)$ vector of coefficients, and $\boldsymbol{SE}$ is a $(D \times 1)$ vector of observed exogenous variables (excluding constants specific to each latent construct). Additionally, $\boldsymbol{\omega}$ is an error term which follows a multivariate standard normal distribution with mean 0 and correlation matrix $\boldsymbol{\Sigma}$ $(L \times L)$ to allow interactions among the unobserved latent constructs. The estimation of the SEM was undertaken using the '*lavaan'* package in R. The absence of latent construct-specific constants in $\boldsymbol{SE}$ and the normalization of the variance of each error term in $\boldsymbol{\omega}$ to one (in Equation (3)) are for identification to accommodate the location-scale invariance of the unobserved latent constructs.

4.2. Spatial-Attitudinal Probit Model

The second step of the proposed model framework involves a spatial-attitudinal multinomial probit model that incorporates an autoregressive structure in the utility function to account for interdependency effects arising from geographical and attitudinal proximity in individuals' commuting mode choices. The effect of social influence originating from spatial and attitudinal proximity will be disentangled by estimating separate coefficients for each dimension. Specifically, the utility functions U_{qj} for each individual q (*1, ..., Q*) and each mode alternative j (*1, 2,..., J; J*=2 in this study) are defined through an autoregressive lag structure as follows:

$$U_{qj} = \rho \sum_{q'}^{Q} w_{qq'} U_{q'j} + \boldsymbol{\beta}' \boldsymbol{x}_{qj} + \varepsilon_{qj}. \tag{4}$$

In this formulation, the autoregressive social lag parameter $\rho(0 < \rho < 1)$ captures the strength of the interdependency effect, while the weight governing the interaction between each pair of individuals q and q' is denoted by the single element $(w_{qq'})$ of the row-normalized multi-dimensional weight matrix $\boldsymbol{W}(Q \times Q)$ with zeros on the diagonal $(w_{qq} = 0; \sum_{q \neq q'}^{Q} w_{qq'} = 1)$.[2] The vector $\boldsymbol{\beta}$ $(A \times 1)$ represents the set of parameters capturing the effect of the exogenous variables $\boldsymbol{x}_{qj}$ $(A \times 1)$, including the alternative specific constant. The set of exogenous covariates includes socioeconomic characteristics of individuals, trip characteristics (trip departure time), alternatives' level-of-service attributes (travel times and costs) and built environment characteristics within a 500-meter radius around the origins and destinations of the trip (number of bus stops). Finally, ε_{qj} is a normally distributed error. ε_{qj} can be aggregated across alternatives for each individual q to obtain $\boldsymbol{\varepsilon}_q = \left(\varepsilon_{q1}, \varepsilon_{q2}, ..., \varepsilon_{qJ}\right)'$ where $\boldsymbol{\varepsilon}_q \sim MNV_J\left(\mathbf{0}, \boldsymbol{\Omega}\right)$. The usual normalization conditions for the estimation of the MNP model will be needed on the covariance matrix $\boldsymbol{\Omega}$ (see Train, 2009 for a detailed discussion). In our case, because we are dealing with only a binary choice, $\boldsymbol{\Omega}$ is innocuously normalized to be an identity matrix of size 2.

In order to write Equation (4) in a more compact matrix format, define $\mathbf{U} = (\mathbf{U}_1, \mathbf{U}_2, ..., \mathbf{U}_Q)'$ a $(QJ \times 1)$ vector, $\boldsymbol{\beta} = \left(\beta_1, \beta_2, ..., \beta_A\right)'$ a $(A \times 1)$ vector, $\mathbf{x}_q = \left(\boldsymbol{x}_{q1}, \boldsymbol{x}_{q2}, ..., \boldsymbol{x}_{qJ}\right)'$ a $(J \times A)$ matrix, $\mathbf{x} = \left(\mathbf{x}_1', \mathbf{x}_2', ..., \mathbf{x}_Q'\right)'$ a $(QJ \times A)$ matrix, and $\boldsymbol{\varepsilon} = (\boldsymbol{\varepsilon}_1, \boldsymbol{\varepsilon}_2, ..., \boldsymbol{\varepsilon}_Q)'$ a $(QJ \times 1)$ vector. Using these stacked matrices, Equation (4) can be rewritten in a more compact manner as follows:

$$\mathbf{U} = \mathbf{S}\left[\mathbf{x}\boldsymbol{\beta} + \boldsymbol{\varepsilon}\right], \tag{5}$$

[2] Note that, as discussed in detail in Bhat et al., 2015b, the social lag parameter is held the same across alternatives in the unordered spatial models. This is because only utility differences matter. At the same time, choosing the base alternative for introducing social dependence (that is, having no social dependence in a base alternative and then introducing alternative-specific social lag parameters on other alternatives) is not innocuous. That is, different results would be obtained by using different alternatives as the base (this exchangeability problem has seldom been discussed in the literature). This issue, as well as the identification problem, are both resolved by specifying the same social lag parameter for all alternatives.

where, $\mathbf{S}$ is a $(QJ \times QJ)$ matrix that can be written as:

$$\mathbf{S} = \left[\mathbf{IDEN}_{QJ} - \left(\rho \boldsymbol{W} \otimes \mathbf{IDEN}_J\right)\right]^{-1} \tag{6}$$

where $\mathbf{IDEN}_{QJ}$ is an identity matrix of dimensions $(QJ \times QJ)$. Based on the above formulation, $\mathbf{U}$ follows a multivariate normal distribution with mean $\tilde{\mathbf{B}} = \mathbf{Sx\beta}$ and covariance matrix $\tilde{\boldsymbol{\Xi}} = \mathbf{S}\left[\mathbf{IDEN}_Q \otimes \boldsymbol{\Omega}\right]\mathbf{S}'$.

4.2.1. Constructing The Weight Matrix

The weight matrix $\boldsymbol{W}$ is defined as a multi-dimensional matrix combining both the spatial $\left(\boldsymbol{D}_{spatial}\right)$ and the attitudinal $\left(\boldsymbol{D}^{l}{}_{attitudinal}\right)$ distance matrices (as proposed by Vinayak *et al.*, 2018). Such a combination is defined as follows:

$$\boldsymbol{W} = exp\left(-\left(\boldsymbol{D}_{spatial} + \sum_{l=1}^{l=L} \kappa_l \boldsymbol{D}^{l}{}_{attitudinal}\right)\right) \tag{7}$$

Here, $\boldsymbol{D}_{spatial}$ is a $(Q \times Q)$ matrix derived from the simple Euclidean distance separation between the residential coordinates of individuals q and q'. On the other hand, the attitudinal distance matrix $\boldsymbol{D}^{l}{}_{attitudinal}$ is a $(Q \times Q)$ matrix that captures, for each latent construct *l*, the distance between each pair of individuals qq' in the attitudinal space. The κ_l coefficients represent a measure of the intensity of interaction among individuals based on proximity in *l*th attitudinal dimension space. The element-by-element exponentiation allows for negative values for κ_l while ensuring positive values for the final weights $(w_{qq'})$. However, the coefficient associated with the spatial distance is fixed to one for identification purposes. Each element in $\boldsymbol{D}^{l}{}_{attitudinal}$ is computed as the absolute difference between the expected values of the corresponding latent variable for each pair of individuals q and q'. Specifically, the $\left(Q \times 1\right)$ vector of predicted values $\hat{\boldsymbol{z}}_l = \left(\hat{z}_{1,l}, \hat{z}_{2,l}, ..., \hat{z}_{Q,l}\right)'$ for each latent variable l obtained from the first phase of the model framework (see Section 4.1) is multiplied by a $\mathbf{1}_{1Q} = \left(1 \times Q\right)$ row vector of ones using a Kronecker product to obtain a $\left(Q \times Q\right)$ matrix $\hat{\mathbb{Z}}_l$, as shown in Equation (8). Then, $\boldsymbol{D}^{l}{}_{attitudinal}$ is obtained by subtracting $\hat{\mathbb{Z}}_l$ and $\left(\hat{\mathbb{Z}}_l\right)'$. Given that we are interested in the magnitude of the differences in latent constructs rather than the directionality, the absolute values of these differences are considered. The result is a $(Q \times Q)$ distance matrix of attitudinal proximity given by:

$$\hat{\mathbb{Z}}_l = \hat{\boldsymbol{z}}_l \otimes \boldsymbol{I}_{1,Q} = \begin{bmatrix} \hat{z}_{1,l} \\ \hat{z}_{2,l} \\ \dots \\ \hat{z}_{Q,l} \end{bmatrix} \otimes \begin{bmatrix} 1 & 1 & \dots & 1 \end{bmatrix}_{1\times Q} \tag{8}$$

$$\boldsymbol{D}^l{}_{attitudinal} = |\hat{\mathbb{Z}}_l - (\hat{\mathbb{Z}}_l)'| = \begin{bmatrix} 0 & |\hat{z}_{1,l} - \hat{z}_{2,l}| & \dots & |\hat{z}_{1,l} - \hat{z}_{Q,l}| \\ |\hat{z}_{2,l} - \hat{z}_{1,l}| & 0 & \dots & |\hat{z}_{2,l} - \hat{z}_{Q,l}| \\ \dots & \dots & \dots & \dots \\ |\hat{z}_{Q,l} - \hat{z}_{1,l}| & |\hat{z}_{Q,l} - \hat{z}_{2,l}| & \dots & 0 \end{bmatrix}_{Q\times Q} \tag{9}$$

It is important to note that that the attitudinal proximity matrix introduced above is based on the expected values of latent constructs rather than their actual values. This approach is primarily due to the fact that the sample is but a random realization of the total population of interest (Vinayak *et al*. 2018). Consequently, it becomes more logically sound to focus on the expected value of a sampled neighbor's latent construct. This construct reflects the broader group of individuals in the population with similar observed characteristics influencing the latent variable of the sampled neighbor.

Before being incorporated in Equation (7), each distance matrix is normalized by dividing each element by the matrix's maximum value to address differences in scale. The resulting weight matrix $\boldsymbol{W}$ is then modified such that its diagonal elements are set to zero and each row is normalized to ensure that each individual receives the same net influence from all the other individuals (the sum of each row is 1).

The parameters to be estimated include the set of $\boldsymbol{\beta}$ coefficients associated with the explanatory variables, including the alternative specific constant, the autoregressive social lag parameter ρ and the set $\boldsymbol{\kappa}\ \{\kappa_1, \kappa_2, ..., \kappa_L\}$ coefficients associated with the attitudinal distance matrices.

4.2.2. Estimation Approach

To construct the likelihood function, we define matrix $\mathbf{M}$ as a $[(J-1)\times Q]\times[J\times Q]$ block diagonal matrix. Each block diagonal corresponds to an individual *q* and consists of $(J-1)$ rows and *J* columns. Specifically, every matrix block is a $(J-1)$ identity matrix with an extra column of -1's inserted at the m_q^{th} column, which represents the observed choice made by individual *q*. Next, let $\mathbf{B} = \mathbf{M}\tilde{\mathbf{B}}$ and $\Xi = \mathbf{M}\tilde{\Xi}\mathbf{M}'$. Also let $\boldsymbol{\theta} = (\boldsymbol{\beta}', \rho, \boldsymbol{\kappa}')'$ be the vector of coefficients to be estimated. The likelihood function $\mathrm{L}(\boldsymbol{\theta})$ for the model takes the following form:

$$\mathrm{L}(\boldsymbol{\theta}) = \Phi_{Q(J-1)}\left(\boldsymbol{\omega}_{\Xi}^{-1}\left(-\mathbf{B}\right), \Xi^{*}\right) \tag{10}$$

where $\Phi_{Q(J-1)}$ is the standard multivariate cumulative distribution of dimension $Q \times (J-1)$, $\boldsymbol{\omega}_{\Xi}^{-1}$ is the inverse of the diagonal matrix of standard deviations of Ξ, and $\Xi^{*} = \boldsymbol{\omega}_{\Xi}^{-1}\,\Xi\,\boldsymbol{\omega}_{\Xi}^{-1}$.

During estimation, the autoregressive social lag parameter is reparametrized as $\rho = \dfrac{1}{1+exp(\breve{\rho})}$ to ensure that ρ (0< ρ <1). A pairwise composite marginal likelihood (CML) inference approach (Bhat, 2011) is employed. Given that the spatial interdependency diminishes rapidly with distance, a threshold distance is determined beyond which the influence of other individuals is assumed to be negligible. This not only helps in reducing the number of pairs considered in the estimation process, but also can increase efficiency of the CML estimator, as discussed in detail in Bhat (2014). The threshold distance follows statistical tests as discussed by Varin and Czado (2010), and Bhat 2014, who suggest that the threshold distance may be determined as the distance which minimizes the trace of the asymptotic covariance matrix. Based on such tests, the optimal threshold distance for considering pairings in the CML approach came out to be 0.75 km. At this distance, the median number of neighboring individuals is 87, ranging from a minimum of 0 (indicating that the agent has no neighbors within the threshold distance) to a maximum of 290.

We tested three different specifications of the model. Specifically, while maintaining consistent explanatory covariates, we estimated one version without social interdependency (the Asocial Probit Model or APM), one with only spatial interdependency (the Spatial Probit Model or SPM), and one with both spatial and attitudinal interdependency effects (the Spatial-Attitudinal Probit Model or SAPM). The selection of the best model was based on the adjusted composite likelihood ratio test (ADCLRT) values. This test value is the equivalent of the log-likelihood ratio test statistic in cases where a composite marginal likelihood inference approach is employed (see Pace *et al.*, 2011 and Bhat, 2014 for further details).

4.3. Elasticity effects of explanatory variables

In discrete choice models (and unlike the case of standard linear regression models), the coefficients from model estimation do not directly provide a sense of the magnitude of the impact of explanatory variables. This is because of the non-linearity of the effect of variables on the probability of choice, causing the marginal impact of a specific explanatory variable for an individual to vary depending upon the magnitude of that variable as well as the levels of each other variable for that individual. Besides, when social influence is considered, the explanatory variable values of other individuals also feature in the effect of any variable for any individual. Consequently, summarizing the effects of explanatory variables requires special techniques in discrete choice models with social influence effects. In particular, a variation in the value of a decision agent's explanatory variable has a twofold impact. It directly modifies the choice probability of that decision agent, while simultaneously (and indirectly through social influence or "ripple wave" effects) impacting the choice probability of other individuals in close proximity (see LeSage and Pace, 2009). To capture this dual effect, we employ the methodology proposed by Bhat (2015). Specifically, we utilize the estimated coefficients to simulate the aggregate mode shares for a base scenario. This involves simulating the utilities for each alternative of each individual 5,000 times (number of draws) and determining the choice probabilities of the two alternatives at each draw. In every draw for each individual, the alternative with the highest probability is designated as the ''chosen'' alternative. The mode choice probabilities for the individual are then estimated by averaging the number of times each alternative is chosen. The aggregate share (across individuals) of each mode can be easily acquired by averaging the probabilities at the individual level for each mode. The pseudo-elasticity effect of an explanatory variable is then determined as follows. When dealing with a continuous explanatory variable, such as travel time and cost, we can assess the impact of a y% variation and differentiate between direct and indirect effects by employing the following procedure:

a) Increase the exogenous variable for the individual of interest by y%, while keeping all other values fixed. Compute the predicted modal probabilities for the individual of interest (as explained in the preceding paragraph), and subsequently calculate the percentage change from the base scenario. Such a percentage change reflects the magnitude of the direct effect for that specific individual.
b) In a similar fashion, determine the percentage change in the predicted modal probabilities resulting from a y% increase in the exogenous variable for all other individuals excluding the individual of interest considered in step (a). The resulting percentage change in modal share represents the magnitude of the indirect effect for the first individual and depends on both the weight matrix $\boldsymbol{W}$ and the social autoregressive parameter ρ.
c) Obtain the overall measures of direct and indirect percentage effects by averaging the individual-specific direct and indirect percentage changes in modal shares, respectively.

For discrete/count explanatory variables, such as workplace/school location characterizations and the number of bus stops in the residential neighborhood, a comparable approach is adopted by switching an individual from one discrete state to another (for discrete exogenous variables) and increasing the count by y units (for count exogenous variables).

5. RESULTS

In this section, we present the results of the final model specification, which was achieved through comprehensive testing of various functional forms and combinations of explanatory variables. This model was adopted based on behavioral considerations, past research, statistical significance, and goodness-of-fit metrics. The final model specification is presented in Table 3 and Table 4.

In Section 5.1 we discuss the structural equation results that link the "perceptions towards sustainable modes" and "environmental awareness" latent constructs to observed demographic variables. This analysis provides insights into the factors influencing the latent constructs, and enables us to estimate the $(Q \times 1)$ expected value vector of predicted values $\hat{\boldsymbol{z}}_l = \left(\hat{z}_{1,l}, \hat{z}_{2,l}, \ldots, \hat{z}_{Q,l}\right)'$ for each attitudinal construct l. As discussed in Section 4.2.1, these expected values are then used to build the attitudinal proximity matrices $\boldsymbol{D}^{l}_{attitudinal}$, which in conjunction with the spatial proximity matrix $\boldsymbol{D}_{spatial}$, are used to calculate the overall weight matrix $\boldsymbol{W}$. The $\boldsymbol{W}$ matrix is a foundational component in the Spatial-Attitudinal Probit Model (SAPM). Next, in section 5.2, we explore the results of the Probit Model, while taking into consideration the interdependency effects among decision-makers arising from their proximity in both the spatial and attitudinal space. Finally, we present an analysis of the marginal effects related to variables that may be influenced by transport-related policies and infrastructure enhancements.

5.1. Structural Equation Model results

Table 3 presents the results of the structural component (top part of Table 3) as well as the measurements component (middle part of Table 3) of the SEM model.

The results indicate a gendered pattern toward both the attitudinal constructs. In particular, compared to women, men are less likely to hold positive perceptions regarding sustainable mobility and environmental awareness. This aligns with previous research (see Xiao and McCright, 2014; Bhat, 2015), and is supported by social-psychological studies. These studies indicate that individuals who identify as women tend to be more altruistic and value the needs of others more so than those who identify as men, which translates to the notion among women that the environment is a collectively shared asset whose quality needs to be preserved for the benefit of all through sustainable and responsible individual actions.

Findings on the effects of age reveal intriguing patterns. Surprisingly, individuals in the youngest age bracket (18 to 30) exhibit less favorable perceptions toward sustainable mobility compared to their older counterparts. This result may be associated with the fact that younger individuals, despite having the possibility of using a car, face greater constraints in accessing a personal vehicle. Additionally, they are more aware of the inconveniences associated with using public transportation due to frequent exposure. At the same time, however, younger individuals (particularly those in the youngest age group of 18 to 30 years) do display a heightened environmental awareness, as has been well established in the literature (see, for example, Clements, 2012, Shi et al., 2016, and Bhat and Mondal, 2022). As future long-term residents of the planet, younger individuals understandably express greater concern about future living conditions, especially those related to climate change, as has been confirmed by a recent global study by Hassim (2021).

The results also reveal a positive effect of having a higher formal educational level, defined here as attaining at least a bachelor's degree, on the awareness of the environmental impact of travel behavior. Supporting this finding, prior research demonstrates a positive correlation between higher formal education and environmental concern (see Franzen and Vogl, 2013; Meyer, 2015; Philippssen et al., 2017; Bhat and Mondal, 2022). One explanation for this association is that higher formal education fosters greater knowledge of environmental issues, ultimately leading to heightened environmental concern, as suggested by Franzen and Vogl, 2013. Moreover, college education has been proven to help the development of critical thinking skills (see Huber and Kuncel, 2016). This enhanced critical thinking ability could potentially lead individuals to critically evaluate and potentially modify their travel behaviors in light of their environmental footprint.

The relationship between personal income and both attitudinal constructs shows a nonmonotonic inverted U-trend. Specifically, individuals in the middle monthly income bracket (€500-€1,500) hold more positive perceptions regarding sustainable modes and higher environmental awareness relative to those with low (under €500) or high (over €1,500) monthly incomes. According to Maslow's (1943) theory of hierarchy of human needs, low-income individuals may not have the luxury of contemplating longer-term and higher-level considerations of moral uprightness (or not) related to the use of sustainable models, because they would be more concerned about lower-level basic biological survival needs. Conversely, high-income individuals may downplay the environmental benefits of sustainable modes to manage any cognitive dissonance they may feel as they strive to signal and project a lifestyle (including car use) of wealth, power/status, privileged access to limited resources, and/or uniqueness in the consumer space (see Chevalier and Gutsatz, 2012).

Lastly, residing in Cagliari positively influences the positive perception associated with sustainable mobility, possibly due to the ease of use of public transit in denser urban settings. However, it is important to acknowledge the potential presence of self selection effects, as some individuals may have chosen to live in Cagliari due to its higher accessibility to public transit.

The results of the MEM component (middle part of Table 3), representing the loadings of the latent constructs on the indicator variables, reveal that all the loadings are intuitive and align with the expectations set by the indicator prompts. Finally, the bottom portion of Table 3 indicates, as expected, a statistically significant and high correlation between the "perception toward sustainable modes" and "environmental awareness" latent constructs.

Table 3 Results of the Structural Equations Model (SEM)

Latent Variable Structural Equation Model	**Perceptions Regarding Sustainable Mobility**		**Environmental awareness**	
	Value	**t-value**	**Value**	**t-value**
Gender (base: woman)				
Man	-0.091	-1.84	-0.207	-4.24
Age (base: over 40 years):				
18 - 30	-0.210	-3.73	0.462	8.31
31 - 40	--	--	0.250	3.25
Formal educational level (base: high school degree or lower)				
At least a bachelor's degree	--	--	0.115	2.21
Personal monthly income (base: outside the range 500 - 1,500 €):				
500 - 1,500 €	0.164	3.08	0.125	2.35
Residential location (base: outside Cagliari)				
City of Cagliari	0.112	2.23	--	--
Latent Variable Measurement Equation Model				
ATT1: I find that using sustainable means of transport instead of the private car is useful.	0.741	55.64	--	--
ATT2: I find that using sustainable means of transport instead of the private car is pleasant.	0.626	42.07	--	--
ATT3: I find that using sustainable means of transport instead of the private car is right.	0.897	77.07	--	--
ENV1: I am aware that the use of private car has negative impacts on the environment and people's health.	--	--	0.818	68.45
ENV2: I am aware that I can personally contribute (by using the car less) to reducing pollution.	--	--	0.888	82.77

ENV3: I feel personally responsible for the environmental problems resulting from the choice of my means of transport.	--	--	0.660	43.99
Correlations among Latent Constructs			0.724 (47.58)	

"--" not statistically significant at 90% confidence level and excluded from specification.

5.2. Probit Model results

Table 4 presents the results of the probit mode choice model, comparing different model structures. It is organized into four broad columns and two row panels. The first column lists the labels of key parameters/data fit measures and the explanatory variables used to determine mode choices (represented by the $\mathbf{x}$ vector in the Methodology section). The second broad column presents the findings from an Asocial Probit Model (APM), the third broad column presents the results of the Spatial Probit Model (SPM) considering only spatial interdependencies, and the fourth broad column presents the model estimation outcomes for a probit model incorporating both spatial and attitudinal interdependencies (that is, the Spatial-Attitudinal Probit Model of the SAPM). Regarding the row panels, the top row panel is dedicated to presenting the social autoregressive parameter ρ and the elements of the $\boldsymbol{\kappa}$ vector providing the intensity of proximity-based interactions in the attitudinal space. The middle panel provides a summary of model properties and goodness-of-fit metrics, while the bottom row panel presents the exogenous variable effects.

5.2.1. Social (Spatial/Attitudinal) Dependency Estimates

The social autoregressive parameter ρ is highly statistically significant in both the SPM and the SAPM models. This finding aligns with previous studies (see, for example, Göetzke, 2008, Sidharthan *et al*., 2011, Walker *et al*., 2011, Wang *et al*., 2015, and Mondal and Bhat, 2022), indicating a strong correlation in the utilities underlying the commute mode choices made by individuals in close proximity. In other words, there is substantial evidence of dyadic interactions between decision-makers located in close proximity, both in the geographic and attitudinal spaces, when selecting their mode of transportation for commuting. Also, the coefficients associated with the attitudinal sources of interdependency $(\kappa_1$ and $\kappa_2)$ are both positive and statistically significant. The positive signs are intuitive and are manifestations of "pull" effects at play in the attitudinal space. Specifically, the more individuals share similar perceptions regarding sustainable mobility environmental awareness, the more they influence each other's commute mode choices. This influence may arise from more frequent interactions among individuals sharing similar opinions on sustainability (*i.e.*, the Echo-chamber effect) or other complex phenomena associated with the passive observation of other individuals in the same perceptual space. The coefficients suggest that attitudinal similarities (represented by matrix $\boldsymbol{D}^{l}_{attitudinal}$), compared to spatial proximity (represented by matrix $\boldsymbol{D}_{spatial}$; the coefficient is fixed to one for identification purposes), influence individuals' mode choices in approximately the same order of magnitude for perceptions toward sustainable modes $(\kappa_1 = 1.191)$, but more intensely for environmental awareness $(\kappa_2 = 2.021)$. This latter finding indicates that the interdependence between two individuals residing in close geographical proximity but with opposing opinions on the environmental impacts of car usage is less pronounced compared to the interdependence observed between individuals living slightly farther apart but sharing similar levels of environmental awareness.

5.2.2. Data Fit Measures

The goodness-of-fit metrics reinforce the importance of considering both spatial and attitudinal interdependence among decision-makers. Since the models are nested, they can be compared using the adjusted composite likelihood ratio test (ADCLRT), which follows a chi-squared distribution (see Bhat, 2014 for details of the ADCLRT computation procedure). The SPM has a single additional parameter (the ρ parameter) relative to the APM, while the SAPM has three additional parameters (the ρ, κ_1, and κ_2 parameters). As shown in the table, the ADCLRT results return a value of 172.93 between the SAPM and the APM, and a value of 51.57 between the SAPM and the SPM. These values strongly reject the APM and SPM in favor of the SAPM at the 99% confidence level. In fact, the results indicate that the superior fit of the SAPM is literally definitive (the ADCLRT values imply that the SAPM rejects the other two models at even the 99.999999999% level).

5.2.3. Exogenous Variable Effects

The coefficients on the exogenous variables in the third row panel of Table 4 represent the effects on utility valuation of the car and public transportation modes. For the sociodemographic and built environment variables, the parameters correspond to the effects on public transportation utility, with the car utility being the base. For the trip characteristics, the parameters are the effects on each of the car and public transportation utilities.

In comparing the different models presented in Table 4, an immediate observation is that the magnitude of effects of several exogenous variables change after considering different sources of interdependency. Specifically, some explanatory variables experience a reduction in their impact (decrease in the magnitude of the absolute coefficient value) when considering spatial/attitudinal interdependency effects. This is evident for variables associated with gender, number of cars per household adult, presence of children in the household, travel time, trip departure time, and the number of bus stops around the trip origin. Conversely, other explanatory variables, including age, income, and the number of bus stops around the trip destination, undergo an increase in the magnitude of their impact. On the other hand, variables such as being a student and travel cost are only marginally affected by the interdependency effects. This observed phenomenon suggests that for certain variables exhibiting a spatial-attitudinal correlated distribution across the sample, the magnitude of their impact diminishes because a portion of this impact is captured by the autoregressive social lag parameter ρ. This means that the APM overestimates the impacts of such variables by ignoring the presence of spatial-attitudinal interactions among individuals. This overestimation effect is particularly high for variables such as the number of bus stops near the trip origin, which is similar for individuals living in the same area, and travel time, which captures other public transit accessibility features, such as bus frequency and walking distance to the bus stop, shared by people in close proximity. Furthermore, since the attitudinal constructs of participants are directly linked to their socioeconomic characteristics, the social lag term ρ may also capture an additional portion of the impact of these characteristics. Conversely, the increase in the magnitude of some variables could be attributed to low spatial correlation in the sample for these variables or to multicollinearity effects, leading to compensatory mechanisms in magnitude values following the introduction of the social interaction terms. As we will discuss in Section 0, addressing interdependency effects not only enables more accurate estimations, but also provides interesting insights into the indirect effects of specific explanatory variables. This, in turn, facilitates a more accurate assessment of the true impact of potential future policy interventions.

Next, based on the results of the SAPM model, we discuss the effects of socioeconomic characteristics, trip characteristics, and built environment attributes on mode choice. First, we note that the alternative-specific constant in the first numeric row of the third row panel of Table 4 does not have any substantive interpretation, and simply adjusts the model to replicate sample shares after consideration of the range of exogenous variables. Regarding gender, men exhibit a lower propensity for choosing public transport compared to women. This finding could be linked to the elevated symbolic value that men typically ascribe to cars (see, for example, Steg, 2005). Additionally, previous analyses conducted in the same study area, as highlighted by Sottile *et al.* (2019), have revealed men's stronger attachment to cars compared to women. In contrast, younger individuals (aged 18-30) and students are more likely to choose public transit relative to older individuals and non-students, respectively. This may be attributed to a combination of factors, such as lower access to vehicles and better transit facilities serving university areas (in ways that are not fully captured by the variables accounting for the "number of cars per adult household member" and other transit service characteristics included in our specification). Household composition is another significant determinant of mode choice. Public transport use is lower among individuals from households with children, likely due to the complex trip chaining required to accommodate children's needs (see, for example, Limtanakool *et al.*, 2006, and Van Eenoo and Boussauw, 2023). Consistent with expectations, the results also indicate that the inclination to use public transport decreases with income, presumably due to factors associated with the typically low symbolic and social status value associated with public transport compared to private cars (see Ashmore *et al.*, 2019, and Moody *et al.*, 2021). Similar to income, the propensity to use public transport diminishes as the number of cars owned per adult in the household increases. This outcome aligns with the findings of a previous study conducted in the same study area (Piras *et al.*, 2022) and with the general concept that higher access to private cars increases the dependency on its use for all purposes (see Bhat, 1998, Culliname and Culliname, 2003, Buehler, 2011, and Saeidizand *et al.*, 2022).

The negative signs associated with the coefficients of level of service characteristics, including travel time and travel cost, are consistent with microeconomic theory. A measure of Value of Travel Time (VTT) can be obtained by dividing the coefficient related to travel time β_{TT} by that of travel cost β_{TC}: $VTT = \frac{\beta_{TT}}{\beta_{TC}} = 9.7$ €$/h$. This value falls within the range of estimates for commute trips in Italy reported in earlier studies (see Shires and de Jong, 2009, and Wardman *et al.*, 2016). Moreover, when the commute trip occurs during the morning peak hours, defined as the period between 7:30 am and 9:30 am, there is a higher likelihood of opting for a car over public transit. This tendency may be linked to the morning peak hour serving as a proxy for other unobserved factors (Mirzaei *et al.*, 2021), such as the congested traffic conditions that could impact the reliability of public transit (see Soza-Parra *et al.*, 2019). This is particularly relevant in the city of Cagliari, where the limited availability of reserved bus lanes and overcrowded buses contributed to increased delays. Additionally, the preference for cars during the morning commute could be attributed to their perceived higher flexibility, comfort (see Börjesson and Rubensson, 2019), as well as schedule reliability, which is particularly important for commute trips (Li *et al.*, 2010).

In terms of built environment measures, the number of bus stops around the origin and destination of the commute trip serve as indicators of public transit accessibility in the individuals' residential and employment areas. The results in Table 4 show a significant increase in the probability of choosing public transport with improved access, consistent with earlier studies (see Limtanakool *et al.*, 2006, and Ding *et al.*, 2017 for examples). However, the results may be influenced by residential self selection effects, whereby individuals with a predisposition for public transit seek out areas with good public transport accessibility (see, for example, Bhat 2015).

Table 4 Models results

	Aspatial Probit Model (APM)		**Spatial Probit Model (SPM)**		**Spatial-Attitudinal Probit Model (SAPM)**	
Social (Spatial/Attitudinal) Dependency Estimates	**Value**	**t-value**	**Value**	**t-value**	**Value**	**t-value**
ρ	--	--	0.384	11.12	0.429	14.06
κ_1 (Perceptions regarding sustainable mobility)	--	--	--	--	1.191	1.82
κ_2 (Environmental awareness)	--	--	--	--	2.021	2.18
Goodness-of-fit measures						
Number of parameters estimated	12		13		15	
Number of observations	2,347		2,347		2,347	
Mean composite log-likelihood value at convergence	-105.261		-103.956		-103.399	
ADCLRT	172.93 ($\chi^2_{3,99\%}$=11.34)		51.57 ($\chi^2_{2,99\%}$=9.21)		--	
Exogenous variables (base: Public Transport)	**Value**	**t-value**	**Value**	**t-value**	**Value**	**t-value**
Alternative specific constant						
Public Transport	0.289	2.31	0.146	1.29	0.161	1.43
Socioeconomic characteristics						
Gender: Man (base: Woman)	-0.225	-6.04	-0.177	-4.74	-0.183	-4.88
Age: 18 – 30 y/o (base: > 30 y/o)	0.267	4.48	0.304	5.08	0.288	4.77
Student (base: non-student)	0.493	8.61	0.525	9.08	0.521	9.00
Presence of at least a child in the household (base: no children)	-0.283	-5.89	-0.182	-3.79	-0.179	-3.75
Personal income: Under 1,500 €/month (base: > 1,500 €/month)	0.332	7.71	0.411	9.60	0.413	9.69
Number of cars per adult household member (continuous)	-1.387	-28.65	-1.218	-24.13	-1.231	-24.43
Trip characteristics						
Travel time (min. x10^{-2}) (generic)	-1.503	-8.15	-1.415	-8.74	-1.389	-8.71

Travel cost (€) (generic)	-0.076	-2.35	-0.073	-2.68	-0.086	-3.20
Departure during the morning peak hour 7:30 – 9:30 (base: outside peak hour)	-0.178	-4.50	-0.170	-4.30	-0.161	-4.09
Built environment						
No. of bus stops in the 500 m around the origin (#/km^2 x10^{-1})	0.199	7.77	0.124	7.13	0.116	7.00
No. of bus stops in the 500 m around the destination (#/km^2 x10^{-1})	0.142	5.72	0.163	6.74	0.167	6.90

Note: All explanatory variables are defined in the Public Transport utility function, with the exception of the generic variables (travel time, travel cost) and the spatial autoregressive parameters.

5.3. "Pseudo-Elasticity" Effects

The use of a social-lag mode choice model in a real-world case study enables the evaluation of the extent to which the impact of a policy intervention can be directly linked to the policy's effects on the targeted populations, as well as the extent to which this impact is mediated (reinforced) by indirect social (spatial and attitudinal) interdependencies. As we discuss later in Section 6, the findings presented in this section have significant implications for understanding the true effectiveness of transportation policies, as well as for the planning of future interventions.

Applying the methodology outlined in Section 4.3, we focus our analysis on the effects of changes in public transport (bus) travel time, bus travel cost, car travel cost, and number of bus stops at the origin and destination of the commute trip. We emphasize these variables because they are critical for assessing the outcomes of future scenarios that involve improvements in the public transportation system and economic interventions aimed at subsidizing public transport (similar to certain initiatives recently implemented in the metropolitan area of Cagliari[3]) or disincentivizing car use, for instance, through the charge of a parking fee, which is not currently applied at the destination (workplaces and university campuses) of most of the individuals in the sample.

For bus travel time, the treatment level we consider is a reduction of 20% across all individuals (the current mean commute bus travel time across all individuals is 36 minutes, and a 20% reduction corresponds to a new mean bus travel time of about 29 minutes). For bus travel cost, the treatment level considered is a 50% reduction, while for car travel cost, it is a 50% increase. The bus cost reduction implies a new mean of about 0.40 euros relative to the current mean of 0.81 euros, while the car cost increase implies a new mean of about 1.90 euros relative to the current mean of 1.25

[3] For an example of similar measures implemented in the metropolitan area of Cagliari, see the website: https://www.comune.cagliari.it/portale/page/it/cagliarinbus__assegnazione_di_contributi_economici_finalizzati_allacquisto_di_abbonamenti_annuali_ordinari_impersonali_e_over_65_emessi_da_ctm_spa?contentId=SRV143500 (last accessed June 24th, 2024)

euros. Additionally, the corresponding treatment level for the number of bus stops (at both the origin and destination ends) is an increase by a count of 5, raising the mean number of bus stops within a 500-meter radius from each end from approximately 20 to 25.

Table 5 shows the results of this analysis, with each row representing a variable for which we calculated direct, indirect, and total average treatment effects (ATEs). In our context, the direct ATEs refer to the changes in mode choice shares resulting from the treatment (for example, a reduction in bus travel time) when it is applied only to the individual of interest, and then averaged across all individuals in the sample. The indirect ATEs correspond to the changes in mode choice shares that occur when the treatment is applied to everyone except the individual of interest, and then averaged across the sample. Lastly, the total ATEs represent the impact of a certain treatment when applied to all individuals simultaneously. It is important to acknowledge that the total effects may not be equal to the sum of direct and indirect effects since this methodological approach deals with percentage changes (refer to Bhat, 2015 for more details). This analysis was conducted for each of the three model structures explored in this study, and the corresponding results are presented in the last three broad columns of the table. Clearly, only the total effect can be assessed in the case of the Aspatial Probit Model (APM). The values in Table 5 only represent the predicted changes in the public transport (bus) mode share within the sample, resulting from the specified variations in the exogenous variables under the "Treatment" column.

In the case of the Spatial-Attitudinal Probit Model (SAPM), the observed indirect effect across all treatments consistently accounts for approximately 40% of the total effect on the share of individuals commuting by public transport. This consistency is expected, given the role of the social lag parameter ρ (which is estimated to be 0.429) in determining the magnitude of social interdependency effects.

Across all three models, the results consistently highlight a notably stronger impact of changes in public transport (bus) travel time compared to travel cost, despite the relatively smaller percentage reduction in travel time (-20%) *versus* the larger percentage reduction in travel cost (-50%). From a policy perspective, while reducing fares represents a straightforward and quick intervention, improving the speed and reliability of public transit has a significantly higher potential for increasing transit ridership compared to fare reductions alone. In fact, previous research has demonstrated that the effect of subsidized public transit fares on ridership, even when made free, highly depends on local factors such as driving conditions and transit service quality (see National Academies of Sciences, Engineering, and Medicine, 2012). Regarding interventions targeting car travel cost, it is evident that increasing travel costs for cars (+50%), such as through the introduction of a parking fee, despite being an unpopular and politically challenging measure, may indeed have a slightly higher impact on modal shift compared to a comparable reduction in public transport cost (-50%). Nevertheless, the impact of such cost-based measures remains relatively low when compared to the effect of interventions targeting public transport travel times. Improving accessibility to public transit by introducing five additional bus stops at the trip origins and destinations exhibits a considerable impact on increasing public transport share for commute trips. These additional bus stops can facilitate a modal shift toward bus usage by reducing walking distances to and from the stops and expanding the set of available bus lines. This can potentially lead to fewer transfers along the route, as well as increased frequency and reliability, which have been proven to highly influence public transport choice among car users (see Outwater *et* al., 2011, and Chakrabarti, 2017). This outcome also underscores the significant importance of ensuring that crucial commute trip attractors, such as universities and employment centers, are easily accessible by public transportation to promote equitable transportation systems (see Rotger and Nielsen, 2015; Saif *et al*., 2019).

In addition to the overall treatment effects that generally followed a similar trend across the three models, the importance of accounting for social interaction effects becomes evident when comparing the total effects obtained from the SAPM with those obtained from the APM. For example, regarding public transport travel time, the total effect captured by the APM is only about 63% of that observed in the model that accounts for both sources of social interdependency effects (+4.76% for the SAPM *versus* +2.98% for the APM). On average, the total effects of the APM amount to approximately 59% of those of the SAPM. This discrepancy highlights how neglecting the impact of spatial and attitudinal interactions in the aspatial model results in overlooking a substantial portion of the potential positive effects of the various policy interventions. At the same time, the model that accounts only for the spatial source of influence (the Spatial Probit Model, SPM) yields estimates that are lower but closer to those of the fully specified model (the SAPM). On average, total effects estimated from the SPM are about 88% of those obtained from the SAPM. This outcome suggests that while considering spatial proximity as a measure of interdependency allows to capture most of the indirect effects, incorporating other sources of attitudinal influence not only enhances the model's performance (as shown in Table 4) but also offers a more nuanced understanding of the true potential effectiveness of transportation policies. This tendency to underestimate the total treatment effects on public transport mode share in models that partially or totally neglect interdependency effects among individuals is consistent across all variables.

Notably, the two variables exhibiting lower variability in total effects are those associated with public transport travel times and the number of public transport stops around individuals' origins and destinations.[4] This result can be attributed to the spatial correlation that exists in these two variables across the sample. Individuals living in close proximity may experience similar out-of-vehicle travel times (due to similar walking and waiting times) and comparable levels of public transport accessibility. Consistent with our discussion in Section 5.2, where we pointed out that the APM might partially account for the spatial correlation of these variables by overestimating their coefficients, the total effects associated with public transport travel time and the number of public transport stops captured by the APM might include some of the indirect effects that the SAPM is able to distinguish from the direct impact of such improvements on each individual's public transport utility. On the other hand, for travel cost variables (both bus and car), which are less correlated with individuals' spatial distribution, the disparity in total effects captured by the APM and the SAPM becomes more pronounced.

Similarly, the smaller difference in the total effects on mode share for bus travel times and the number of bus stops at origins and destinations, compared to bus and car travel cost, between the SPM and the SAPM, could stem from the potential correlation between attitudinal constructs (namely perceptions regarding sustainable mobility and environmental awareness) and bus travel times and public transport accessibility. Individuals facing longer bus travel times and greater difficulty accessing this service (because of longer walking and waiting times) may develop lower levels of satisfaction with public transportation, leading to more negative attitudes toward this travel option (De Vos *et al*., 2022). On the other hand, previous studies have found that travel cost is a less prominent characteristic in shaping attitudes toward public transportation (see Beirão *et al*., 2007, and Guiver, 2007). Given the aforementioned spatial correlation present in public transport travel time and the number of bus stops across the sample, the reduced discrepancy in SPM's and SAPM's total effects for these two variables might be explained by the SPM partially capturing the attitudinal source of influence within the spatial-only lag parameter. The SAPM, on the other hand, could more effectively distinguish between spatial and attitudinal sources of influence. Conversely, the lower correlation between travel costs and attitudinal constructs might explain the heightened gap between SPM's and SAPM's total effects.

[4] In the case of bus travel time and the number of bus stops at origins and destinations APM's and SPM's total effects are, on average, 66.5% and 95.1% of SAPM's. In the case of bus and car travel cost APM's and SPM's total effects are, on average, 51.2% and 80.0% of SAPM's.

Table 5 Effect of interventions on public transport (bus) share

Exogenous variables	Treatment	Aspatial Probit Model (APM)	Spatial Probit Model (SPM)			Spatial-Attitudinal Probit Model (SAPM)		
		Total effect	Direct effect	Indirect effect	Total effect	Direct effect	Indirect effect	Total effect
Bus travel time	-20%	2.98%	2.83%	1.73%	4.55%	2.71%	1.96%	4.76%
Bus travel cost	-50%	0.84%	0.80%	0.49%	1.33%	0.97%	0.69%	1.64%
Car travel cost	+50%	1.31%	1.26%	0.76%	2.02%	1.47%	1.06%	2.56%
No. of bus stops 500 m around both origin and destination	+5	4.74%	3.95%	2.42%	6.37%	3.88%	2.89%	6.74%

6. POLICY IMPLICATIONS

The findings of this study hold significant implications for quantifying the impacts of potential transportation policies, particularly those aimed at improving public transportation services.

First, the pseudo-elasticity effects discussed in Section 5.3 suggest that, across all modeling approaches considered, interventions that improve the speed, reliability, and accessibility to public transport have the strongest impact on increasing ridership compared to cost-based interventions that either incentivize bus usage or disincentivize private vehicle use. Consequently, policymakers should prioritize investments and initiatives that directly target the quality of public transport services in order to improve its overall attractiveness and competitiveness as a viable alternative to private vehicles. This can be achieved through infrastructure or service-oriented improvements. Infrastructure measures include implementing dedicated bus lanes and signal prioritization. Service-related improvements could involve increasing the frequency of public transport services, introducing real-time information systems, and integrating public transport with other modes of transportation, such as park-and-ride facilities and bike-sharing systems.

Second, our results show that the indirect effects, which could be attributed to the "ripple wave" effect, accounted for approximately 40% of the total effects captured by the Spatial-Attitudinal Probit Model (SAPM). This implies that the impact of a policy aimed at increasing transit usage extends not only to those directly affected by the intervention but also significantly influences individuals in close physical and attitudinal proximity through indirect "channels". This insight holds significance for planning limited-budget incentive interventions and information campaigns. Such initiatives may prove more effective when targeted towards specific individuals in diverse neighborhoods or social groups, as opposed to addressing all components of a particular neighborhood or social group collectively. For instance, promoting public transit usage through a fare-free program might yield better results if specifically tailored to needy households residing in various neighborhoods, rather than being directed at all households within a specific neighborhood.

Third, the statistical significance and high magnitude of the autoregressive social lag coefficient highlights the interconnected nature of individual choices. Neglecting to account for this interdependence may introduce bias into the estimation of parameters, as well as lead to an incorrect evaluation of possible future scenarios. This is exemplified by the results in Table 5, which show that the total effects captured by the SAPM consistently are higher than those captured by the other two model structures. In this context, if the City of Cagliari were to evaluate measures aimed at reducing its carbon footprint, the simple Aspatial Probit Model (APM) would underestimate the positive effect of a measure aimed at shifting people from car use to public transport through, for example, an increase in bus travel speed. In contrast, the SAPM would provide policymakers a more accurate estimate of the actual increase in public transport use and the subsequent reduction in emissions, possibly helping the city demonstrate its ability to meet environmental requirements.

Finally, incorporating a dual source of interaction, which considers similarity in attitudes as an additional factor influencing individuals' mode choices, reveals that the influence from individuals with similar attitudes toward sustainable mobility and similar levels of environmental awareness is important and could potentially exceed the impact of physical proximity. This outcome underscores the substantial correlation that exists between attitudes and transportation mode choices, emphasizing the significant opportunity that targeted behavioral change interventions may have in enhancing public transit usage. For instance, the reinforcing nature of observing and perceiving fellow neighbors making similar transportation choices could be effectively leveraged through behavioral campaigns aimed at highlighting positive peer behaviors and their underlying drivers. By showcasing neighbors with similar travel patterns (*e.g.*, traveling from the same neighborhood to the city center) who choose sustainable travel options to do good for the environment, such campaigns can inspire others to prioritize environmentally friendly modes, thereby contrinibuting to a more livable city.

7. CONCLUSIONS

This study examined the impact of spatial and attitudinal interdependency on individuals' commuting mode choices, using data obtained from a travel survey conducted in the Metropolitan area of Cagliari between October 2019 and January 2020. While attempts have been made to model these spatial and attitudinal interdependency effects in the field of travel behavior, our research introduces a novel social autoregressive travel mode choice model, the Spatial-Attitudinal Probit Model (SAPM), applied to a real case study. The use of a dual source of interaction allows for a deeper understanding of the nature of social influence on travel behavior. Notably, our results indicate that attitudinal similarities, especially those associated with environmental awareness, may exert a more significant impact compared to spatial proximity.

Additionally, our study contributes to the literature on social influence by analyzing the direct and indirect effects of potential transportation policies aimed at enhancing public transport attractiveness through improvements in its rapidness, affordability, and accessibility, or decreasing car attractiveness through the increase in its travel costs. Results indicate that approximately 40% of the total effect of such interventions can be attributed to social interaction among decision-makers. By leveraging this "Ripple wave" effect as a result of the dyadic interactions among individuals, more effective targeted interventions may be put in place.

The analysis in this study may be extended to consider a wider array of transportation modes as well as non-commute travel mode choices. More broadly, we hope that the methodology developed in this paper will further accelerate the adoption of social influence models in travel behavior analyses, based on both spatial and attitudinal proximity effects.

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References

Abou-Zeid, M., Schmöcker, J.D., Belgiawan, P.F., Fujii, S. (2013). Mass effects and mobility decisions. *Transportation Letters,* 5, 115–130. https://doi.org/10.1179/1942786713Z.00000000011

Alves, H. (2018). Sharing Rare Attitudes Attracts. *Personality and Social Psychology Bulletin*, 44(8), 1270–1283. https://doi.org/10.1177/0146167218766861

Ashmore, D. P., Pojani, D., Thoreau, R., Christie, N., & Tyler, N. A. (2019). Gauging differences in public transport symbolism across national cultures: implications for policy development and transfer. *Journal of Transport Geography*, 77, 26–38. https://doi.org/10.1016/j.jtrangeo.2019.04.008

Bachmann, F., Hanimann, A., Artho, J., & Jonas, K. (2018). What drives people to carpool? Explaining carpooling intention from the perspectives of carpooling passengers and drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, 59, 260–268. https://doi.org/10.1016/j.trf.2018.08.022

Bamberg, S., Schmidt, P. (2003). Incentives, morality, or habit? Predicting students' car use for University routes with the models of Ajzen, Schwartz, and Triandis. *Environment and Behavior*, 35(2), 264–285. https://doi.org/10.1177/0013916502250134

Bamberg, S., Hunecke, M., & Blöbaum, A. (2007). Social context, personal norms and the use of public transportation: Two field studies. *Journal of Environmental Psychology*, 27(3), 190–203. https://doi.org/10.1016/j.jenvp.2007.04.001

Beirão, G., Sarsfield Cabral, J.A. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transp. Policy* 14, 478–489. https://doi.org/10.1016/j.tranpol.2007.04.009

Belgiawan, P. F., Schmöcker, J. D., Abou-Zeid, M., Walker, J., & Fujii, S. (2017). Modelling social norms: Case study of students' car purchase intentions. *Travel Behaviour and Society*, 7, 12–25. https://doi.org/10.1016/j.tbs.2016.11.003

Bhat, C.R. (1998). Analysis of travel mode and departure time choice for urban shopping trips. *Transp. Res. Part B Methodol*. 32B, 361–371. https://doi.org/10.1016/s0191-2615(98)00004-6

Bhat, C.R. (2011). The maximum approximate composite marginal likelihood (MACML) estimation of multinomial probit-based unordered response choice models. *Transp. Res. Part B Methodol*. 45, 923–939. https://doi.org/10.1016/j.trb.2011.04.005

Bhat, C.R. (2014). The composite marginal likelihood (CML) inference approach with applications to discrete and mixed dependent variable models. *Found. Trends Econom*. 7, 1–117. https://doi.org/10.1561/0800000022

Bhat, C. R. (2015). A new spatial (social) interaction discrete choice model accommodating for unobserved effects due to endogenous network formation. *Transportation*, 42(5), 879–914. https://doi.org/10.1007/s11116-015-9651-9

Bhat, C. R., Dubey, S. K., Alam, M. J. bin, & Khushefati, W. H. (2015b). A new spatial multiple discrete-continuous modeling approach to land use change analysis. *Journal of Regional Science*, 55(5), 801–841. https://doi.org/10.1111/jors.12201

Bhat, C.R., Pinjari, A.R., Dubey, S.K., Hamdi, A.S. (2016). On accommodating spatial interactions in a Generalized Heterogeneous Data Model (GHDM) of mixed types of dependent variables. *Transp. Res. Part B Methodol*. 94, 240–263. https://doi.org/10.1016/j.trb.2016.09.002

Bhat, C. R., Mondal, A. (2022). A New Flexible Generalized Heterogeneous Data Model (GHDM) with an Application to Examine the Effect of High Density Neighborhood Living on Bicycling Frequency. *Transportation Research Part B: Methodological*, 164, 244–266. https://doi.org/10.1016/j.trb.2022.09.004

Bond, R.M., Fariss, C.J., Jones, J.J., Kramer, A.D.I., Marlow, C., Settle, J.E., Fowler, J.H. (2012). A 61-million-person experiment in social influence and political mobilization. *Nature* 489, 295–298. https://doi.org/10.1038/nature11421

Börjesson, M., Rubensson, I. (2019). Satisfaction with crowding and other attributes in public transport. *Transport policy*, 79, 213-222. https://doi.org/10.1016/j.tranpol.2019.05.010

Brock, W. A., & Durlauf, S. N. (2001). Discrete Choice with Social Interactions. *Review of Economic Studies* (Vol. 68). https://academic.oup.com/restud/article/68/2/235/1523094

Buehler, R. (2011). Determinants of transport mode choice: a comparison of Germany and the USA. *J. Transp. Geogr*. 19, 644–657. https://doi.org/10.1016/j.jtrangeo.2010.07.005

Carrus, G., Passafaro, P., Bonnes, M. (2008). Emotions, habits and rational choices in ecological behaviours: The case of recycling and use of public transportation. *J. Environ. Psychol*. 28, 51–62. https://doi.org/10.1016/j.jenvp.2007.09.003

Chakrabarti, S. (2017). How can public transit get people out of their cars? An analysis of transit mode choice for commute trips in Los Angeles. *Transp. Policy* 54, 80–89. https://doi.org/10.1016/j.tranpol.2016.11.005

Cherchi, E. (2017). A stated choice experiment to measure the effect of informational and normative conformity in the preference for electric vehicles. *Transportation Research Part A: Policy and Practice*, 100, 88–104. https://doi.org/10.1016/j.tra.2017.04.009

Chevalier, M., Gutsatz, M. (2012). Luxury retail management: How the world's top brands provide quality product and service support. John Wiley & Sons, Singapore.

Cinelli, M., de Francisci Morales, G., Galeazzi, A., Quattrociocchi, W., Starnini, M. (2021). The echo chamber effect on social media. *Proc. Natl. Acad. Sci. U. S. A*. 118. https://doi.org/10.1073/pnas.2023301118

Clements, B. (2012). Exploring public opinion on the issue of climate change in Britain. *British Politics*, 7(2), 183–202. https://doi.org/10.1057/bp.2012.1

Cruwys, T., Bevelander, K.E., Hermans, R.C.J. (2015). Social modeling of eating: A review of when and why social influence affects food intake and choice. *Appetite* 86, 3–18. https://doi.org/10.1016/j.appet.2014.08.035

Cullinane, S., Cullinane, K. (2003). Car dependence in a public transport dominated city: Evidence from Hong Kong. *Transp. Res. Part D Transp. Environ*. 8, 129–138. https://doi.org/10.1016/S1361-9209(02)00037-8

De Vos, J., Singleton, P.A., Gärling, T. (2022). From attitude to satisfaction: introducing the travel mode choice cycle. *Transp. Rev*. 42, 204–221. https://doi.org/10.1080/01441647.2021.1958952

Ding, C., Wang, D., Liu, C., Zhang, Y., Yang, J. (2017). Exploring the influence of built environment on travel mode choice considering the mediating effects of car ownership and travel distance. *Transp. Res. Part A Policy Pract*. 100, 65–80. https://doi.org/10.1016/j.tra.2017.04.008

Dugundji, E.R., Walker, J.L. (2005). Discrete Choice with Social and Spatial Network Interdependencies. *Transp. Res. Rec*. https://doi.org/10.1177/0361198105192100109

Eesley, C., Wang, Y. (2017). Social influence in career choice: Evidence from a randomized field experiment on entrepreneurial mentorship. *Res. Policy* 46, 636–650. https://doi.org/10.1016/j.respol.2017.01.010

Franzen, A., Vogl, D. (2013). Two decades of measuring environmental attitudes: A comparative analysis of 33 countries. *Global Environmental Change*, 23(5), 1001–1008. https://doi.org/10.1016/j.gloenvcha.2013.03.009

Göetzke, F. (2008). Network effects in public transit use: Evidence from a spatially autoregressive mode choice model for New York. *Urban Studies*, 45(2), 407–417. https://doi.org/10.1177/0042098007085970

Guiver, J.W. (2007). Modal talk: Discourse analysis of how people talk about bus and car travel. *Transp. Res. Part A Policy Pract*. 41, 233–248. https://doi.org/10.1016/j.tra.2006.05.004

Hassim, A. (2021). Why younger generations are more willing to change in the name of sustainability. GreenBiz.com. Available at: https://www.greenbiz.com/article/why-youngergenerations-are-more-willing-change-name-sustainability

Huber, C. R., Kuncel, N. R. (2016). Does College Teach Critical Thinking? A Meta-Analysis. *Review of Educational Research*, 86(2), 431–468. https://doi.org/10.3102/0034654315605917

Kim, J., Rasouli, S., & Timmermans, H. (2014). Expanding scope of hybrid choice models allowing for mixture of social influences and latent attitudes: Application to intended purchase of electric cars. *Transportation Research Part A: Policy and Practice*, 69, 71–85. https://doi.org/10.1016/j.tra.2014.08.016

Kim, S., Rasouli, S. (2022). The influence of latent lifestyle on acceptance of Mobility-as-a-Service (MaaS): A hierarchical latent variable and latent class approach. *Transp. Res. Part A Policy Pract*. 159, 304–319. https://doi.org/10.1016/j.tra.2022.03.020

Kowald, M., Frei, A., Hackney, J., Illenberger, J., Axhausen, K.W. (2009). The influence of social contacts on leisure travel: A snowball sample of personal networks. *12th Int. Conf. Travel Behav. Res. (IATBR 2009).*

LeSage, J., & Pace, R.K. (2009). Introduction to Spatial Econometrics (1st ed.). *Chapman and Hall/CRC*. https://doi.org/10.1201/9781420064254

Li, Z., Hensher, D.A., Rose, J.M. (2010). Willingness to pay for travel time reliability in passenger transport: A review and some new empirical evidence. *Transp. Res. Part E Logist. Transp*. Rev. 46, 384–403. https://doi.org/10.1016/j.tre.2009.12.005

Limtanakool, N., Dijst, M., & Schwanen, T. (2006). The influence of socioeconomic characteristics, land use and travel time considerations on mode choice for medium- and longer-distance trips. *Journal of Transport Geography*, 14(5), 327–341. https://doi.org/10.1016/j.jtrangeo.2005.06.004

Loureiro, S.M.C., Costa, I., Panchapakesan, P. (2017). A passion for fashion: The impact of social influence, vanity and exhibitionism on consumer behaviour. *Int. J. Retail Distrib. Manag*. 45, 468–484. https://doi.org/10.1108/IJRDM-11-2016-0202

Manski, C.F. (1993). Identification of Endogenous Social Effects: The Reflection Problem. *The review of economic studies*, 60(3), 531-542. https://doi.org/10.2307/2298123

Maslow, A. H. (1943). A theory of human motivation. *Psychological Review*, 50(4), 370–396. https://doi.org/10.1037/h0054346

Meyer, A. (2015). Does education increase pro-environmental behavior? Evidence from Europe. *Ecological Economics*, 116, 108–121. https://doi.org/10.1016/j.ecolecon.2015.04.018

Mirzaei, E., Kheyroddin, R., Mignot, D. (2021). Exploring the effect of the built environment, weather condition and departure time of travel on mode choice decision for different travel purposes: Evidence from Isfahan, Iran. *Case Stud. Transp. Policy* 9, 1419–1430. https://doi.org/10.1016/j.cstp.2021.05.002

Mondal, A., Bhat, C. R. (2022). A spatial rank-ordered probit model with an application to travel mode choice. *Transportation Research Part B: Methodological*, 155, 374–393. https://doi.org/10.1016/j.trb.2021.12.008

Moody, J., Farr, E., Papagelis, M., Keith, D.R. (2021). The value of car ownership and use in the United States. *Nat. Sustain*. 4, 769–774. https://doi.org/10.1038/s41893-021-00731-5

Murray, S.J., Walton, D., Thomas, J.A. (2010). Attitudes towards public transport in New Zealand. *Transportation (Amst)*. 37, 915–929. https://doi.org/10.1007/s11116-010-9303-z

National Academies of Sciences, Engineering, and Medicine. (2012). Implementation and Outcomes of Fare-Free Transit Systems. *Washington, DC: The National Academies Press*. https://doi.org/10.17226/22753.

Outwater, M.L., Spitz, G., Lobb, J., Campbell, M., Sana, B., Pendyala, R., Woodford, W. (2011). Characteristics of premium transit services that affect mode choice. *Transportation (Amst)*. 38, 605–623. https://doi.org/10.1007/s11116-011-9334-0

Pace, L., Salvan, A., Sartori, N. (2011). Adjusting Composite Likelihood Ratio Statistics. Statistica *Sinica*, 21(1), 129–148. http://www.jstor.org/stable/24309265

Páez, A., Scott, D. M. (2007). Social influence on travel behavior: A simulation example of the decision to telecommute. *Environment and Planning A*, 39(3), 647–665. https://doi.org/10.1068/a37424

Philippssen, J. S., Soares Angeoletto, F. H., and Santana, R. G. (2017). Education level and income are important for good environmental awareness: A case study from south Brazil. *Ecología Austral*, 27(1), 39-44

Piras, F., Sottile, E., Tuveri, G., Meloni, I. (2022). Does the joint implementation of hard and soft transportation policies lead to travel behavior change? An experimental analysis. *Res. Transp. Econ*. 95, 101233. https://doi.org/10.1016/j.retrec.2022.101233

Rotger, G.P., Nielsen, T.S. (2015). Effects of job accessibility improved by public transport system: Natural experimental evidence from the copenhagen metro. *Eur. J. Transp. Infrastruct. Res*. 15, 419–441. https://doi.org/10.18757/ejtir.2015.15.4.3090

Saeidizand, P., Fransen, K., Boussauw, K. (2022). Revisiting car dependency: A worldwide analysis of car travel in global metropolitan areas. *Cities 120*, 103467. https://doi.org/10.1016/j.cities.2021.103467

Saif, M.A., Zefreh, M.M., Torok, A. (2019). Public transport accessibility: A literature review. Period. *Polytech. Transp. Eng*. 47, 36–43. https://doi.org/10.3311/PPtr.12072

Saleem, M.A., Ismail, H., Ali, R.A. (2021). Actions speak louder than words: Investigating the interplay between descriptive and injunctive norms to promote alternative fuel vehicles. *Sustain*. 13. https://doi.org/10.3390/su13179662

Shi, J., Visschers, V. H. M., Siegrist, M., & Arvai, J. (2016). Knowledge as a driver of public perceptions about climate change reassessed. *Nature Climate Change*, 6(8), 759–762. https://doi.org/10.1038/nclimate2997

Shires, J.D., de Jong, G.C. (2009). An international meta-analysis of values of travel time savings. *Eval. Program Plann*. 32, 315–325. https://doi.org/10.1016/j.evalprogplan.2009.06.010

Sidharthan, R., Bhat, C., Pendyala, R., & Goulias, K. (2011). Model for children's school travel mode choice. *Transportation Research Record*, 2213, 78–86. https://doi.org/10.3141/2213-11

Sottile, E., Piras, F., Meloni, I. (2019). Could a New Mode Alternative Modify Psycho-Attitudinal Factors and Travel Behavior? *Transp. Res. Rec*. 2673, 94–106. https://doi.org/10.1177/0361198119843478

Soza-Parra, J., Raveau, S., Muñoz, J.C., Cats, O. (2019). The underlying effect of public transport reliability on users' satisfaction. *Transp. Res. Part A Policy Pract*. 126, 83–93. https://doi.org/10.1016/j.tra.2019.06.004

Steg, L., (2005). Car use: Lust and must. Instrumental, symbolic and affective motives for car use. *Transp. Res. Part A Policy Pract*. 39, 147–162. https://doi.org/10.1016/j.tra.2004.07.001

Train, K. E. (2009). Discrete choice methods with simulation. *Cambridge university press*. https://cambridge.org/9780521747387

Van Eenoo, E., Boussauw, K. (2023). "That's not feasible without a car": An exploration of car-dependent practices. *Transp. Policy* 144, 1–10. https://doi.org/10.1016/j.tranpol.2023.09.021

Van Lange, P.A.M., Joireman, J., Parks, C.D., Van Dijk, E., 2013. The psychology of social dilemmas: A review. *Organ. Behav. Hum. Decis. Process*. 120, 125–141. https://doi.org/10.1016/j.obhdp.2012.11.003

Varin, C., Czado, C. (2010). A mixed autoregressive probit model for ordinal longitudinal data. *Biostatistics*, 11(1), 127–138. https://doi.org/10.1093/biostatistics/kxp042

Vinayak, P., Dias, F. F., Astroza, S., Bhat, C. R., Pendyala, R. M., Garikapati, V. M. (2018). Accounting for multi-dimensional dependencies among decision-makers within a generalized model framework: An application to understanding shared mobility service usage levels. *Transport Policy*, 72, 129–137. https://doi.org/10.1016/j.tranpol.2018.09.013

Walker, J. L., Ehlers, E., Banerjee, I., Dugundji, E. R. (2011). Correcting for endogeneity in behavioral choice models with social influence variables. *Transportation Research Part A: Policy and Practice*, 45(4), 362–374. https://doi.org/10.1016/j.tra.2011.01.003

Wang, C. H., Akar, G., Guldmann, J. M. (2015). Do your neighbors affect your bicycling choice? A spatial probit model for bicycling to The Ohio State University. *Journal of Transport Geography*, 42, 122–130. https://doi.org/10.1016/j.jtrangeo.2014.12.003

Wardman, M., Chintakayala, V.P.K., de Jong, G. (2016). Values of travel time in Europe: Review and meta-analysis. *Transp. Res. Part A Policy Pract*. 94, 93–111. https://doi.org/10.1016/j.tra.2016.08.019

Xiao, C., McCright, A.M., 2014. A Test of the Biographical Availability Argument for Gender Differences in Environmental Behaviors. Environ. Behav. 46, 241–263. https://doi.org/10.1177/0013916512453991

Zhang, D., Schmöcker, J. D., Fujii, S., & Yang, X. (2016). Social norms and public transport usage: empirical study from Shanghai. *Transportation*, 43(5), 869–888. https://doi.org/10.1007/s11116-015-9625-y

Appendix A

Table A Confirmatory Factory Analysis and Cronbach's alphas

Factor	Items	Loading	Cronbach's alpha
LV1 Attitude toward sustainable mobility	ATT1: I find that using sustainable means of transport instead of the private car is useful.	0.646	0.704
	ATT2: I find that using sustainable means of transport instead of the private car is pleasant.	0.570	
	ATT3: I find that using sustainable means of transport instead of the private car is right.	0.808	
LV2 Environmental awareness	ENV1: I am aware that the use of private car has negative impacts on the environment and people's health.	0.745	0.715
	ENV2: I am aware that I can personally contribute (by using the car less) to reducing pollution.	0.826	
	ENV3: I feel personally responsible for the environmental problems resulting from the choice of my means of transport.	0.587	