The Effect of Implementing an App-Based Voluntary Travel Behavior Change Program. A Case Study in Cagliari, Italy

Italo Meloni, Tariq Naveed, Francesco Piras(✉), Eleonora Sottile, and Giovanni Tuveri

Università degli Studi di Cagliari, Cagliari, Italy
francesco.piras@unica.it

Abstract. Implementing Voluntary Travel Behavioral Change (VTBC) programs aimed at encouraging sustainable mobility faces three key challenges: biased samples resulting from self-selected participants, reliance on one-time surveys instead of panel data to track behavioral changes, and limited use of econometric models. Recent research suggests that GPS-based panel data can provide more accurate evaluations. This study evaluates a smartphone-based VTBC program designed to encourage behavioral change among drivers in the metropolitan area of Cagliari. The VTBC program was implemented through Personalized Travel Plans (PTPs), which suggested alternatives to car travel, and included gamification elements. Different econometric models were constructed to assess the program's effects. A joint binary-ordered logit model was used to simultaneously estimate the probability of participating in the program and the likelihood of making sustainable tours after receiving a PTP and engaging with gamification. Additionally, a multinomial logit model was developed to analyze tour mode choice probabilities before and after the intervention. The model results indicate that receiving the intervention reduces the probability of car use. Furthermore, in addition to the intervention itself, factors such as car ownership and psychological variables significantly influence both the likelihood of participating in the program and the adoption of more sustainable travel behaviors.

Keywords: Personalized travel plan · Choice modeling · Sustainable mobility · Smartphone app

1 Introduction

The growing dependence on cars has led to significant environmental, social, and economic issues, including air pollution, traffic congestion, and declining public health. Reducing car dependency has been a key focus of researchers aiming to achieve sustainability goals. A cost-effective and efficient approach to reducing car use is the implementation of informative measures, also known as Voluntary Travel Behavior Change (VTBC) programs, which aim to convince individuals to change their current travel behavior by providing them with information, assistance, motivation, or incentives [1].

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Over the last 20 years, various VTBC programs have been implemented worldwide, and all these experiences have reported a reduction in private car use of between 5% and 15% [2]. Despite their benefits and the reported results, the outcomes of VTBC program implementations often suffer from incorrect evaluation procedures, both in terms of the sample used for analysis and the methodology applied. These methodological inaccuracies prevent comparisons between programs implemented in different contexts and make it difficult to determine with certainty whether such measures can truly lead to long-term behavioral change.

One of the main issues in past research is its focus solely on the behavior of individuals who agreed to participate in the VTBC program, which may result in a biased sample [3]. Specifically, those who are already more predisposed, psychologically or for other reasons, to adopt behavioral change may be more likely to participate, particularly when active involvement is required. Therefore, the impact of behavioral change should be assessed not only in relation to those who actively participate in the program but also in relation to the entire sample reached, so as to prevent overestimating the effects of the informative measure.

In many previous studies, behavioral change evaluation has been conducted using one-shot Revealed Preference surveys, where respondents were simply asked whether they had changed their behavior (yes/no) and which mode they had switched to. However, as suggested by Stopher *et al.* [4] and implemented in more recent studies [3, 5], it is important to assess behavioral change using panel data. Ideally, this data should be collected through GPS-based applications, allowing for the evaluation of behavioral change over multiple days and a larger number of trips or tours.

Furthermore, it is essential to evaluate behavior changes induced by informative measures using econometric models to assess the impact of each variable, whether subjective or objective, on travel behavior change, as discussed by Piras *et al.* [7]. Some recent studies have tried to do this, but they have either relied on Stated Intention data [8] or used one-shot Revealed Preference surveys [7], failing to analyze trips and tours over multiple days. Others have evaluated trips over multiple days but only measured distances traveled [3], without considering mode choice. To our knowledge, the only studies to have addressed this comprehensively are those of Sanjust di Teulada *et al.* [6] and Meloni *et al.* [9], where behavioral change was analyzed through tour-based assessments.

Given the above discussion, the present study aims to evaluate the effectiveness of a smartphone-based VTBC program designed to encourage behavioral change among a sample of drivers. The study was conducted in Cagliari, Italy. Two different econometric models were developed to investigate the factors influencing both the propensity to participate in the program and changes in travel behavior.

The remainder of the paper is organized as follows: Sect. 2 provides a review of the literature on voluntary travel behavior change programs. Section 3 outlines the methodology, including data collection and the modeling approach used in the study. Section 4 presents the results of the aggregate analysis and econometric model estimations. Finally, Sect. 5 concludes with key findings and policy implications.

2 Literature Review

One of the most successful soft measures for reducing car use is VTBC programs, whose main idea is 'directly contacting individuals with the offer of information, assistance, incentives, and motivation to enable them to voluntarily change their choices' [10]. The concept of VTBC has been applied in Australia and Germany since the 1980s and was adopted in the United Kingdom in the late 1990s [11]. In Australia, VTBC programs have been shown to reduce vehicle kilometers traveled (VKT) by 14–23% and car travel by 10% [12]. The TravelSmart program led to a 13% lasting reduction in car travel [13]. In Cambridge, Australia, TravelSmart achieved a 7% reduction in car use and a 17% increase in the use of sustainable modes of transport [13]. In the UK, VTBC programs showed a 4–5% reduction in VKT by car, a 0–30% reduction in car travel for work, an 8–15% reduction in car use for school trips, and a 7–15% reduction in household car use. Additionally, marketing campaigns resulted in a 1–5% increase in bus trips and a 12% reduction in car trips [13, 14]. In Hampshire, the TravelSmart/IndiMark initiative led to a 6% increase in public transport trips [13, 14]. In the USA, VTBC initiatives achieved an 8% reduction in car use, while in Canada the reduction was 10% [13]. In Japan, VTBC programs resulted in a 7% reduction in car trips and a 69% increase in bus trips [15].

Technology can play a significant role in implementing Voluntary Travel Behavior Change (VTBC) programs, and recent studies have demonstrated the use of smartphones in this context. Geng *et al.* [16] used the smartphone app WeChat to conduct information-based intervention trials. Jariyasunant *et al.* [17] developed a computational travel feedback system called "Quantified Traveler", which was shown to reduce driving. Tsirimpa *et al.* [18] employed the "OPTIMUM" mobile app to evaluate the effectiveness of reward-based interventions in promoting sustainable multimodal travel choices. Sanjust Di Teulada *et al.* [19] utilized a device called the Activity Locator, a GPS active logger integrated with a GPS-enabled mobile phone, to monitor individuals participating in a program designed to nudge users toward using a light rail line. Finally, Sottile *et al.* [20] used the smartphone application "IPET", an evolution of the Activity Locator employed in [19], to implement a VTBC program among a sample of university students, aiming to influence their commuting travel behavior.

Studies that implemented VTBC programs through smartphone applications reported varying results and employed different methodologies to assess their effectiveness. Jariyasunant *et al.* [17] found that the average weekly distance driven decreased by 33%. Using a Structural Equation Model, they also observed that changes in travel behavior were influenced by shifts in attitudes and social norms, which were, in turn, shaped by peer influence and increased awareness resulting from the app's feedback features. Sanjust di Teulada *et al.* [19] reported that 27% of participants changed their travel behavior as a result of the program. Building on this, Sanjust di Teulada *et al.* [6] used the same dataset to model the choice of using light rail at the tour level with a binary probit model. Their findings indicated that, in addition to the program's informational content, participants' interest in reducing transport-related emissions significantly contributed to behavioral change. Sottile *et al.* [20] observed an 8.1% shift toward sustainable transportation modes among students after completing an app-based VTBC program. They also found that the program enhanced participants' awareness of CO_2

emissions and calorie expenditure, as well as their perceived behavioral control over sustainable mobility choices.

A less explored topic in the literature concerns the willingness to use smartphone apps designed to encourage changes in travel behavior. Most existing studies focus only on the general propensity to use travel apps, rather than those specifically aimed at behavior change. These studies have employed various psychological theories, including the Unified Theory of Acceptance and Use of Technology (UTAUT2) [21, 22], the Technology Acceptance Model (TAM) [23–25], the Expectation Confirmation Model (ECM) [25], the Technology Continuance Theory (TCT) [26], and the Theory of Planned Behavior (TPB) [23]. Findings from these studies suggest that the willingness and intention to use such apps can be influenced by several factors: environmental concerns positively affect the likelihood of continued app use [22, 27]; user interaction plays a key role in satisfaction and thereby increases app usage [21, 24–26, 28]; ease of use [23, 24] and perceived usefulness [24, 28] are important; attitudes toward the app [26, 29] and social interaction [28] also positively influence use. Additionally, perceived enjoyment enhances both user attitude [26] and perceived usefulness [23], and habits [28] further support continued usage. In contrast, concerns about privacy risks negatively impact app usage [24, 30].

3 Methodology

3.1 Data Collection

The data for this study was drawn from the Svoltiamo project, conducted in the metropolitan city of Cagliari, Italy, by the Inter-university Center for Economic Research and Mobility (CIREM) at the University of Cagliari. The goal of the project was to implement a Voluntary Travel Behavior Change (VTBC) program aimed at raising community awareness about the negative impacts of intensive private car use. This initiative sought to reduce the use of private cars and promote sustainable transportation modes, including active mobility, public transit, and shared mobility. To achieve effective results in terms of voluntary behavioral change, the program included extensive promotional, informational, and communication efforts. These efforts were facilitated through a dedicated web portal and a smartphone application, highlighting sustainable travel alternatives, their advantages over private car use, for both individuals and the broader community, and providing incentives (mobility vouchers) for those who adopted sustainable transportation.

The program was structured into several phases:

- Phase 1: Conducted between October 2019 and January 2020, this phase involved a large-scale marketing campaign. It included advertisements in local newspapers and on television, billboards along major roads, postcards distributed at key city locations, social media promotions, and email outreach. The target audience included employees of the Municipality of Cagliari, the Sardinia Region, and students and staff of the University of Cagliari, all project partners. The campaign aimed to raise public awareness and encourage people to complete a questionnaire about their travel habits. A total of 4311 responses were collected.

- Phase 2: This phase was intended to begin in March 2020 and involved the implementation of the VTBC program at a personal level. However, due to restrictions imposed in response to the COVID-19 pandemic, the program was suspended.
- Phase 3: Between March and May 2022, all individuals who had completed the Phase 1 questionnaire were re-contacted. They were asked again about their travel behavior and invited to participate in a VTBC program involving the use of a smartphone app. A total of 735 individuals completed the Phase 3 questionnaire, and 347 were selected for the program based on eligibility criteria: regular car use for work or study and working within the city of Cagliari.
- Phase 4: Following analysis of the Phase 3 data, all 347 eligible participants were officially invited to take part in the VTBC program.
- Phase 5: The core VTBC program was implemented between June and November 2022 using the Svoltiamo smartphone app. The app tracked participants' daily trips and activities to generate a Personalized Travel Plan (PTP), recommending sustainable commuting alternatives tailored to individual travel patterns. It provided insights into travel costs, time, CO_2 emissions, and calories burned for both car and suggested sustainable commuting alternatives on a daily, weekly, monthly, and yearly basis. The app also featured a gamification system, rewarding users for adopting sustainable behaviors. This phase lasted 2 weeks and included the following steps:

  – Week 1: Participants used the app for at least 3 days to track their current trips and activities. At the end of the week, they received a Personalized Travel Plan.
  – Week 2: Participants continued using the app for another 3 days to assess whether the Personalized Travel Plan influenced their travel behavior. During this week, users began earning reward points for using sustainable modes of transportation.

  Points earned during the second week could be redeemed for public transport and car-sharing passes, as well as bonuses toward the purchase of a bicycle or e-scooter. In total, 83 individuals participated in Phase 5, and of those, only 41 used the app consistently during both weeks.

Table 1 reports the characteristics of the sample used in the analysis presented in this paper.

Table 1. Data Sample

Sample Description	Individuals invited to participate in the VTBC program		Individuals who used the smartphone app in both weeks	
	[N]	[%]	[N]	[%]
Total User	347	100	41	100
Gender				

(*continued*)

Table 1. (*continued*)

Sample Description	Individuals invited to participate in the VTBC program		Individuals who used the smartphone app in both weeks	
	[N]	[%]	[N]	[%]
Male	193	55.62	20	48.78
Female	154	44.38	21	51.22
Education				
Elementary middle school	7	2.02	2	4.88
High school	97	27.95	10	24.39
Degree	160	46.11	22	53.66
PhD	83	23.92	7	17.07
Income (€)				
Income 0–1000	44	12.68	6	14.63
Income 1000–2000	213	61.38	23	56.10
Income 2000+	90	25.94	12	29.27
Age (Years)				
Age (18–30)	49	14.12	6	14.63
Age (30–40)	55	15.85	6	14.63
Age (40–50)	105	30.26	16	39.02
Age (50–60)	119	34.29	11	26.83
Age (60+)	19	5.48	2	4.88

3.2 Psychological Variables

An important aspect of the study involved investigating the role of psychological variables in travel behavior change. To this end, in the survey conducted during Phase 3 of the study, we asked individuals to indicate their level of agreement with a series of psycho-social statements related to environmental concern and sustainable mobility, using a 5-point Likert scale. The distribution of responses for the whole sample of 347 individuals is presented in Table 2.

To derive latent variables for inclusion in the econometric model specifications, we conducted a confirmatory factor analysis, which revealed five distinct latent constructs:

- Social norm.
- Environmental concern.
- Attitude toward sustainable mobility.
- Perceived behavioral control of sustainable mobility.
- Intention to use private car.

Table 2. Distribution of psychological variables (347 individuals)

Item	1	2	3	4	5
Social norm					
Most people I know think I should use sustainable transport modes instead of a private car	24.21%	25.65%	31.99%	12.97%	4.61%
Most people I know use sustainable transport modes instead of a private car	41.79%	40.06%	11.82%	2.88%	3.17%
Environmental concern					
I feel personally responsible for the environmental problems resulting from the choice of my means of transport.	6.34%	7.78%	18.73%	45.24%	20.75%
I feel personally responsible for the problems resulting from road congestion, space occupancy and car accidents in my city.	9.51%	14.12%	20.75%	40.92%	13.54%
I am aware that the use of private car has negative impacts on the environment and people's health.	0.58%	2.31%	6.92%	35.45%	53.89%
I am aware that I can personally contribute (by using the car less) to reducing pollution.	1.15%	2.88%	7.49%	38.33%	48.99%
Attitude toward sustainable mobility					
I find that using sustainable means of transport instead of the private car is useful.	2.59%	5.48%	12.10%	41.79%	37.18%
I find that using sustainable means of transport instead of the private car is pleasant.	4.90%	13.26%	23.63%	32.56%	24.78%
I find that using sustainable means of transport instead of the private car is right.	1.15%	2.59%	9.51%	41.79%	44.09%
Perceived behavioral control toward sustainable mobility					
It would be easy for me to use sustainable means of transport.	29.11%	28.24%	17.00%	18.73%	6.63%
I am sure that in the next week I can use sustainable means of transport.	30.26%	22.77%	21.61%	16.14%	8.36%
For me using sustainable means of transport is possible.	22.19%	20.17%	17.87%	23.63%	15.56%
Intention to use private car					
During the next 2 weeks I do not intend to use sustainable transport modes instead of the car	7.78%	18.16%	23.92%	24.50%	25.07%

(*continued*)

Table 2. (*continued*)

Item	1	2	3	4	5
During the next 2 weeks I intend to use a private car	2.02%	2.88%	13.26%	37.46%	43.80%
I am not interested in using sustainable transport modes during the next 2 weeks	5.19%	7.78%	33.72%	20.46%	32.56%

The latent variables were then calculated using the Anderson–Rubin regression method, which generates scores with a mean of 0, a standard deviation of 1, and no correlation among them.

3.3 Tour Data Preprocessing

One crucial element of the analysis in this paper is the examination of tours undertaken during Phase 5 of the VTBC program. The analysis of these tours required extensive data preprocessing.

Tours are defined as chains of trips that start and end at the same location. In this study, we focused exclusively on home-based tours, meaning tours that begin and end at the individual's home. The data preprocessing was carried out in the following steps: (1) exclusion of individuals with incomplete daily activity logs or missing time usage data; (2) correction of users' location statuses based on GPS coordinates; (3) correction of distances using GPS data; (4) exclusion of individuals who stayed away from home overnight; (5) exclusion of tours with undefined purposes; (6) correction of data entry errors and undefined travel modes.

After preprocessing, we identified the main mode of transportation and the main purpose for each tour. The prevalent mode was defined as the mode by which the user covered the greatest distance during the tour. To determine the main purpose of each tour, we analyzed tour stops, defined as locations where individuals paused during the tour for specific activities such as leisure, study, work, or errands. If a tour included a stop for study or work, the main purpose of the tour was classified as work/study. Otherwise, the tour's purpose was assigned based on the stop with the longest duration.

The total number of tours considered in the study is 270: 137 in the first week and 133 in the second week.

3.4 Modeling Methodology

Data from the smartphone-based VTBC program were used to build discrete choice models with two main goals: (1) to identify the factors influencing individuals' likelihood of using the smartphone application and choosing sustainable transportation modes after receiving a Personalized Travel Plan; (2) to assess the relative importance of the Personalized Travel Plan, compared to other factors, in the decision to undertake a tour using sustainable transportation. To address the first objective, we construct a joint binary ordered logit model. To address the second objective, we construct a multinomial logit model. All the models were estimated using PandasBiogeme software [31].

3.4.1 Joint Binary Ordered Logit Model

To analyze the factors influencing the decision to actively participate in the VTBC program and, among participants, the factors influencing the choice to undertake sustainable tours after receiving, in the second week of the program, the informational measure and gamification, we specify and estimate a joint binary ordinal logit model. This model consists of two distinct latent equations: a logit selection equation, which models the decision to participate in the program; an ordered logit equation, which models, conditional on participation, the number of sustainable tours undertaken during the second week of the program.

Let q indicate an individual, where $q = 1, 2, \ldots, Q$. In this model $Q = 347$. Let p_q be a binary variable equal to 1 if individual q choose to participate in the VTBC program and 0 if he chooses not to participate. p_q is linked to a latent variable p_q^* through the following measurement equation: $p_q = 1$ if $\mathrm{p}_\mathrm{q}^* > 0$, otherwise $p_q = 0$. The latent variable p_q^* representing the propensity to participate in the VTBC program is expressed as:

$$\mathrm{p}_\mathrm{q}^* = \beta_o + \boldsymbol{\beta}\boldsymbol{x}_q + \boldsymbol{\beta}^*\boldsymbol{LV}_q + \varepsilon_q \tag{1}$$

where β_o is a constant, $\boldsymbol{x}_q$ is a vector of observed variables and $\boldsymbol{LV}_q$ is a vector of psychological variables. $\boldsymbol{\beta}$ and $\boldsymbol{\beta}^*$ are vectors of model parameters to be estimated, while ε_q is an independently and identically distributed (i.i.d.) logistic error term. The choice probabilities for participation and non-participation are thus given by:

$$\begin{cases} \Pr(p_q = 1) = \frac{\exp(\beta_o + \boldsymbol{\beta}\boldsymbol{x}_q + \boldsymbol{\beta}^*\boldsymbol{LV}_q)}{1+\exp(\beta_o + \boldsymbol{\beta}\boldsymbol{x}_q + \boldsymbol{\beta}^*\boldsymbol{LV}_q)} \\ \Pr(p_q = 0) = \frac{1}{1+\exp(\beta_o + \boldsymbol{\beta}\boldsymbol{x}_q + \boldsymbol{\beta}^*\boldsymbol{LV}_q)} \end{cases} \tag{2}$$

Conditional on $p_q = 1$, we define y_q as a discrete variable representing the number of sustainable tours completed by individual q, where: $y_q = 0$, for 0 sustainable tours; $y_q = 1$ for 1–2 sustainable tours; $y_q = 2$ for more than 2 sustainable tours. y_q is generated by an ordered logit model via the latent propensity y^*:

$$y_q^* = \gamma_o + \boldsymbol{\gamma}\boldsymbol{x}_q + \boldsymbol{\gamma}^*\boldsymbol{LV}_q + \upsilon_q \tag{3}$$

With γ_o being a constant, $\boldsymbol{\gamma}$ and $\boldsymbol{\gamma}^*$ being vectors of parameters to be estimated, υ_q is an independently and identically distributed (i.i.d.) logistic error term. The observed outcomes y_q are related to the latent utility y_q^* through the following equations:

$$y_q = \begin{cases} 0 & if\ \rho_0 < y_q^* \le \rho_1 \\ 1 & if\ \rho_1 < y_q^* \le \rho_2 \\ 2 & if\ \rho_2 < y_q^* \le \rho_3 \end{cases} \tag{4}$$

where $\boldsymbol{\rho} = (\rho_0, \ldots, \rho_2)$ is a vector of threshold parameters ($\rho_0 = -\infty$ and $\rho_3 = \infty$; $\rho_1 = 0$; $\rho_1 < \rho_2$). The ordered logit probabilities are given by:

$$\Pr(y_q) = \begin{cases} \Pr\left(y_q = 0 \middle| \boldsymbol{x}_q, \boldsymbol{LV}_q, p = 1\right) = \frac{e^{\left[-y_q^*\right]}}{1+e^{\left[-y_q^*\right]}} \\ \Pr\left(y_q = 1 \middle| \boldsymbol{x}_q, \boldsymbol{LV}_q, p = 1\right) = \frac{e^{-\left[y_q^*\right]}}{1+e^{-\left[y_q^*\right]}} - \frac{e^{-\left[y_q^*-\rho_2\right]}}{1+e^{-\left[y_q^*-\rho_2\right]}} \\ \Pr\left(y_q = 2 \middle| \boldsymbol{x}_q, \boldsymbol{LV}_q, p = 1\right) = 1 - \frac{e^{-\left[y_q^*-\rho_2\right]}}{1+e^{-\left[y_q^*-\rho_2\right]}} \end{cases} \tag{5}$$

Under the assumption that ε_q and υ_q are uncorrelated error terms, the likelihood function L is given by:

$$\mathrm{L} = \prod_{\mathrm{q}=1}^{\mathrm{Q}} \prod_{\mathrm{j}=0}^{2} \left(\Pr\left(\mathrm{p_q} = 0\right)\right)^{1-\mathrm{p_q}} \times \left(\Pr\left(\mathrm{p_q} = 1\right) \Pr\left(\mathrm{y_q} = \mathrm{j}\right)\right)^{\mathrm{p_q} \times 1_{\mathrm{y_q}=\mathrm{j}}} \quad (6)$$

where $\mathbf{1}_{y_q=j}$ is an indicator function equal to 1 if $y_q = j$, and 0 otherwise.

3.4.2 Multinomial Logit Model

To measure the effect of the Personalized Travel Plan and gamification on mode choice, we construct a multinomial logit model. In particular, the model estimates the probability of choosing a mode of transportation, private car, public transport, or active mobility, using data collected before (Week 1) and after (Week 2) the intervention. The sample used to estimate this model consists of the set of tours made by the 41 individuals who participated in the program and consistently used the smartphone application during both the first and second weeks (270 tours in total).

Let be n an index for tour and i an index for mode of transportation. The utility function of mode i for tour n can be given by U_{in}:

$$U_{in} = V_{in} + \varepsilon_{in} = \beta_{i,0} + \boldsymbol{\beta_{i,SE}} \boldsymbol{SE}_n + \boldsymbol{\beta_{i,LV}} \boldsymbol{LV}_n + \boldsymbol{\beta_{i,T}} \boldsymbol{T}_n + \beta_{\mathrm{i,week}}{}^{*} week_n + \varepsilon_{in} \quad (7)$$

where $\boldsymbol{SE}_n$ is a vector of socio-demographic characteristics for the individual who made the tour, $\boldsymbol{LV}_n$ is a vector of psychological variables, $\boldsymbol{T}_n$ is a vector of tour-specific characteristics, $week_n$ is a dummy variable which is equal to 1 if tour was made in Week 2 (after PTP and gamification) and 0 if made in Week 1 (before PTP and gamification), $\beta_{i,0}, \boldsymbol{\beta_{i,SE}}, \boldsymbol{\beta_{i,LV}}, \boldsymbol{\beta_{i,T}}, \beta_{i,week}$ are parameters to be estimated and ε_{in} is an independently and identically distributed Gumbel error term.

The probability that the tour is undertaken using mode is:

$$P_{in} = \frac{e^{V_{in}}}{\sum_{cj \in C} e^{V_{jn}}} \quad (8)$$

4 Results

4.1 Analysis of Participation in the Program and Travel Behavior Change

Table 3 presents the analysis of participation in the VTBC program. It can be observed that the majority of those invited to participate (76.1%) chose not to join the program and did not use the smartphone application.

Table 4 displays the number of sustainable tours made in the second week by those who used the application (83 individuals). As noted above, most of the sample did not change their travel behavior, either due to a lack of interest in the program after the first week of participation (42 individuals, 50.6%) or for other reasons (12 individuals, 14.5%). Some individuals partially changed their travel behavior, making one or two sustainable tours during the week (20 individuals, 24.0%), while others made more than

Table 3. Decision to participate in the VTBC program and app usage

	[N]	[%]
Individuals that did not participate in the VTBC program	264	76.1%
Individuals that did not use the application in either the first or second week	42	12.1%
Individuals that used the application in first week and second week	41	11.8%
Total	347	100%

Table 4. Descriptive analysis of number of sustainable tours made after receiving PTP and gamification (second week)

	[N]	[%]
Individuals that did not use the app in either the first or second week	42	50.6%
Individuals that made 0 sustainable tours in second week	12	14.5%
Individuals that made 1 sustainable tour in second week	10	12.0%
Individuals that made 2 sustainable tours in second week	10	12.0%
Individuals that made 3 sustainable tours in second week	6	7.2%
Individuals that made more than 3 sustainable tours in second week	3	3.6%

two sustainable tours in the second week (9 individuals, 10.8%). If we consider the share of individuals who partially or completely changed their travel behavior relative to the total sample of 357 individuals, we obtain a change rate of 8.35%, which is consistent with findings from previous research [2].

It is interesting to analyze how travel behavior changed among individuals who consistently used the application during both weeks (Table 5). The number of car tours decreased from 94 in the first week to 68 in the second week, with the modal share of private car use dropping from 68.6% to 51.1%. The mode of transportation that increased the most was public transportation, rising from 14.6% to 26.3%, while the share of active mobility also increased, from 16.8% to 22.6%. This shift is partly due to the long distances of some trips, which may have made it unfeasible to complete them using active mobility.

Table 5. Number of tours by mode in first and second week

		Private car	Public transport	Active mobility	Total
First week	[N]	94	20	23	137
	[%]	68.6%	14.6%	16.8%	100.0%
Second week	[N]	68	35	30	133
	[%]	51.1%	26.3%	22.6%	100.0%

In terms of changes in total distance traveled by different modes of transportation (Table 6), it can be observed that the total tour distance by car decreased from 2376.72 km in the first week to 1148.27 km in the second week (–51.7%). In contrast, the total travel distance by public transport increased from 360.60 to 620.39 km (+72%). Active mobility also saw an increase in total tour distance, rising from 52.11 to 106.31 km (+104%). Interestingly, in the second week, the average distance per tour using active mobility also increased, from 2.27 to 3.54 km.

Table 6. Total and average distance (km) for prevalent tour mode

	Total travel distance [km]	Average travel distance [km]	Average number of stops [N]
First week			
Private car	2376.72	25.28	1.81
Public transport	360.60	18.03	1.40
Active mobility	52.11	2.27	1.17
Second week			
Private car	1148.27	16.89	1.58
Public transport	620.39	17.73	1.46
Active mobility	106.31	3.54	1.13
Difference first week second week			
Private car	−51.7%	33.2%	−12.9%
Public transport	72.0%	−1.7%	4.1%
Active mobility	104.0%	56.4%	−3.5%

4.2 Results of Joint Binary Ordinal Logit Model

Table 7 displays the results of joint binary ordinal model. In the first section of the model factors influencing the adoption of the app for sustainable transportation are shown. Individuals with higher car ownership and those with longer commuting distances were less likely to use the app, likely due to their reliance on private transport. In contrast, Environmental concern had a positive effect, indicating that individuals more conscious of sustainability were more inclined to engage with the app, corroborating findings of past research [22, 27].

In the second section of Table 6 results of the ordered model, modeling the choice of the number of sustainable tours in the second week of the program, are reported. The likelihood of choosing a sustainable tour mode in week 2 decreased as the number of cars in the household increased, suggesting that individuals with greater access to private vehicles are less inclined to choose sustainable modes of transport [32]. Conversely, the likelihood of choosing sustainable transport increased for individuals whose origin

Table 7. Model results of joint binary ordinal logit model

Estimation report		
Null log likelihood	−423.418	
Final log likelihood	−254.132	
Akaike Information Criterion	526.2649	
Bayesian Information Criterion	560.9088	
Estimated parameters	**Value**	**Robust t-stat**
App Use		
Constant	−0.33	−1.00
Distance [km]	−0.01	−1.27
No. of cars in the household	−0.37	−2.32
Environmental Concern	0.28	2.08
Sustainable Mode in Week 2		
Constant	0.54	0.71
No. of cars in the household	−1.01	−2.40
Origin other than Cagliari	2.00	4.29
Intention to use a private car	−0.43	−1.70

was outside of Cagliari. Psychological factors also play a crucial role. In our case, the Intention to use private car emerged as a significant barrier to its adoption. This negative coefficient suggests that individuals who express a stronger intention to avoid sustainable transport, often due to their dependence on private vehicles, are less likely to choose it [32].

4.3 Results of Multinomial Logit Model

To model the effects of Personalized Travel Planning (PTP) and gamification, we included only users who participated in both weeks of app monitoring. The resulting dataset comprised 41 users and 270 tours. Model results are reported in Table 8.

The likelihood of choosing active mobility over private transport decreased for longer tour distances. This is because active mobility, unlike motorized modes, requires physical effort. As the distance increases, the comfort and feasibility of active mobility decrease due to the physical demands involved.

Tour mode choices were also influenced by socioeconomic (SE) variables. Regarding gender, females were more likely to use public transport than males. This finding aligns with the studies by Masoumi *et al.* [33] and Limtanakool *et al.* [34], which suggest that males often perceive private transport as a status symbol. Income levels also significantly influenced mode choice. Individuals with lower incomes (0–1000 €) were more likely to choose public transport over private transport, consistent with previous research [35]. In contrast, individuals with average incomes (1000–2000 €) were more inclined to

Table 8. Results of Multinomial Logit Model.

Estimation report	**Multinomial Logit Model**	
Null log likelihood	−256.48	
Final log likelihood	−150.9579	
Akaike Information Criterion	327.9159	
Bayesian Information Criterion	374.6954	
Estimated parameters	**Value**	**Robust t-stat**
Constant Active Mobility	−1.02	−1.44
Constant Public Transport	−2.40	−3.55
Active Mobility		
Income (1000–2000) €	1.50	2.96
Distance [km]	−0.46	−3.46
Possession of the bicycle	2.79	5.25
PTP-Week	0.73	1.77
Public Transport		
Gender (Male = 1)	−0.82	−2.08
Commuting Tour (yes = 1, no =0)	1.21	2.31
Income 0–1000 €	2.43	3.73
No. of cars in the household	−0.44	−1.67
Tour Stop (greater than 2 stops)	−1.18	−2.12
PTP-Week	1.28	3.26
Intention to use a private car	−0.85	−4.32

choose active mobility. Car ownership had a significant impact on mode choice. As car ownership increased, so did travel flexibility and the ability to make multiple stops, advantages not offered by public transport. Accordingly, in our model the likelihood of choosing public transport over private transport decreased with car ownership, as indicated by a negative coefficient. Conversely, owning a bicycle significantly increased the likelihood of choosing active mobility over both private and public transport.

The complexity of tours, measured by the number of stops, also affected mode choice. For tours with more than two stops, the likelihood of choosing public transport over private transport decreased, due to the limited flexibility and fixed routes of public transport. However, for tours whose main purpose was commute, a positive coefficient was observed, suggesting that public transport remains a viable option for more direct, routine commuting trips.

The parameters associated with the dummy variable for the temporal factor were positive for both public transport and active mobility. This suggests that the PTP and gamification features were effective in reducing the likelihood of using private cars, consistent with previous studies [6, 20]. Notably, the parameter associated with public

transport in the utility function had a larger magnitude than that for active mobility. This indicates a greater impact of the program in promoting a shift toward public transport. One possible explanation is that active mobility was not a feasible alternative for many tours due to their distance. Note that we also attempted to interact the variable related to temporal factors with other variables, such as the purpose of the tours and the number of stops. However, these interaction terms were not statistically significant.

Psychological variables were also analyzed. Specifically, we found that the Intention to use a private car reduced the likelihood of choosing public transport [32]. This suggests that individuals lacking motivation or interest in sustainable transportation are more likely to rely on private vehicles. Although other psychological variables (Perceived Behavioral Control, Social Norms, Attitude, and Environmental Concern) were included in the model, they were not statistically significant. This is likely due to their correlation with Intention to use a private car, as postulated by the Theory of Planned Behavior [36].

5 Conclusions

Previous studies on Voluntary Travel Behavior Change (VTBC) often relied on self-selected participants, used one-time surveys rather than panel data to track behavioral changes, and lacked rigorous econometric modeling. This study addresses these limitations by using GPS-based data collected over multiple days and applying econometric mode choice models.

The purpose of this study is to evaluate the effectiveness of a smartphone-based VTBC program, specifically implemented through Personalized Travel Planning, aimed at encouraging behavioral change among a sample of drivers. The program was implemented in Cagliari, Italy, and data was collected as part of the "Svoltiamo" project, carried out by the Inter-university Center for Economic Research and Mobility (CIREM) at the University of Cagliari.

The effect of the PTP was evaluated by modeling mode choice using both socioeconomic and psychological variables. App usage and the decision to undertake sustainable tours following the PTP intervention were analyzed using a joint binary-ordered model. Additionally, the mode of each tour (e.g., active or public transport) was modeled based on tour complexity using a Multinomial Logit (MNL) model.

The results indicate that the likelihood of using the app for sustainable travel decreases with higher car ownership and longer travel distances, as these factors diminish the attractiveness of sustainable alternatives. However, environmental awareness positively influences app usage, suggesting that individuals with strong sustainability values are more likely to engage with the program. These findings carry clear policy implications: enhancing public awareness of the environmental impact of car use and promoting environmental consciousness could increase participation in VTBC programs.

The MNL model reveals that socioeconomic characteristics significantly influence mode choice. Women are more likely to use public transport, low-income individuals tend to prefer it due to affordability, and middle-income groups are more inclined toward active mobility. Beyond economic and spatial constraints, the model results also highlight the significant role of psychological factors, particularly the Intention to use a private car, in shaping mobility choices.

While the likelihood of choosing active or public transport increases compared to private car use, the PTP was not effective in shifting mode choices among those with a higher intention to use the car. This can be largely attributed to time constraints and the inadequacy of the sustainable transportation system of the city of Cagliari. To better support behavior change in this group, more customized PTP solutions should incorporate real-time travel alternatives that effectively reduce travel time and cost. Additionally, improvements in public transport infrastructure, such as shorter travel times and reduced service headways, are essential. For active mobility, the presence of a well-connected network would further enhance the effectiveness of PTP interventions.

This study is not without limitations. First, it relies on a small sample size, which limits the generalizability of the findings. Future research should aim to include larger and more diverse samples to better capture a broader range of socioeconomic characteristics. Second, although incentives were incorporated into the VTBC program to promote sustainable travel, their specific effects were not explicitly analyzed. Future studies could examine the distinct impact of these incentives in greater detail.

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