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Abstract

This study aimed at assessing the role of travel information provision on behavioral changes in daily mobility in the metropolis of Montpellier in France. We focused on commuter behavior using data collected through an online survey on mobility behavior during the summer of 2015. We found that while 73% of commuters respondents use travel information sources, only 31% of them declared any mobility behavior change. This study explores the impact of specific factors such as sociodemographic variables (e.g., age and gender) and transportation habits (e.g., public transportation pass, travel time, and safety margin). As an operational measure of the prudent behavior, safety margin highlights the threshold effect of travel information provision on behavioral changes. Indeed, three commuter profiles can be distinguished according to their prudence levels: chronically non-prudent, reasonably prudent, and excessively prudent. Finally, the study highlights that travel information provision alone may not be enough to induce a shift in behavioral changes among commuters toward more environment-friendly modes of transportation.

Keywords: Travel information; Mobility behavior change; Commuter; Transportation habit; Sustainable urban mobility;

JEL classification: R40; R48; C35; D80

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Abstract

This study aimed at assessing the role of travel information provision on behavioral changes in daily mobility in the metropolis of Montpellier in France. We focused on commuter behavior using data collected through an online survey on mobility behavior during the summer of 2015. We found that while 73% of commuters respondents use travel information sources, only 31% of them declared any mobility behavior change. This study explores the impact of specific factors such as socio-demographic variables (e.g., age and gender) and transportation habits (e.g., public transportation pass, travel time, and safety margin). As an operational measure of the prudent behavior, safety margin highlights the threshold effect of travel information provision on behavioral changes. Indeed, three commuter profiles can be distinguished according to their prudence levels: chronically non-prudent, reasonably prudent, and excessively prudent. Finally, the study highlights that travel information provision alone may not be enough to induce a shift in behavioral changes among commuters toward more environment-friendly modes of transportation.

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1 Introduction

In recent years, public authorities have faced two significant challenges within their territories: increasing or maintaining, high mobility levels and reducing external transportation costs while focusing on air pollution and CO_2 emissions. The transportation sector is the largest greenhouse gas (GHG) emitter in Europe, with 28% of emissions in 2017, and accounting for 37.5% of total emissions in France (Muntean et al., 2018). Looking closely at the distribution of GHG emissions within the transportation sector, CITEPA (Technical Reference Center for Air Pollution and Climate Change) (2016) notes that 56% of transportation emissions in France are owed to private vehicles, while only 22% are owed to heavy goods vehicles. This high proportion of emissions from personal vehicles is connected to commuting, posing a challenge to public authorities and a requirement to act.

Public authorities have several tools to reduce external transportation costs of commuting, such as tolls, taxes, and bans. However, these standard tools do not work well in France. Even though individuals generally understand the requirement to reduce the negative environmental externalities generated by private cars, such options tend to be unpopular. Thus, public authorities consider local policies to reduce transportation's negative externalities while maintaining individual mobility, such as sustainable mobility plans.[1] The emergence of digital technologies, connected objects, and, more particularly, smartphones, makes it possible to rethink these public policies in favor of sustainable mobility. Kay et al. (2010) identified six cases in which information and communications technology (ICT) projects can have an impact on mobility: reducing the need to travel (e.g., working from home), influencing the choice of travel mode, changing driver behavior (e.g., eco-driving), changing vehicle behavior, increasing vehicle load factor (e.g., car sharing, high occupancy vehicle lanes), and increasing network efficiency (e.g., congestion charging). In general, these policies inform individuals with the aim to encourage them to shift to or adopt environment-friendly behaviors.

[1]See *Article 51 of La Loi de Transition Energétique pour la Croissance Verte.* `https://www.legifrance.gouv.fr/eli/loi/2015/8/17/DEVX1413992L/jo/texte`

Travel information and behavior change issues are a familiar topics in the transportation literature. This study aims to understand how any kind of travel information (e.g., pre-trip, *en-route* information) induces commuter mobility behavior changes. This study is original because of the choice of Montpellier, which is in a uniquely paradoxical situation for several reasons. First, Montpellier, a medium-sized city located in the south of France with about a population of approximately 285,121, experiences acute traffic congestion. In 2015,[2] according to the Traffic Index Ranking by TomTom®, Montpellier was ranked as the third most congested city in France, just behind Marseille and Paris, and ahead of Bordeaux and Lyon.[3] The additional travel time due to congestion is estimated to be approximately 28% for commuting; it is 38% and 26% for Marseille and Lyon, respectively. Second, Montpellier was one of the first cities in France to develop tramway services. The first tramway line was introduced in 2000. In 20 years, three additional lines have been built for a total of 57.9 km of infrastructure (the third largest French network after Lyon and Bordeaux, without considering the Paris Region).[4] Finally, Montpellier has set a high target for reducing car use for commuting – less than 50% of the market share by the end of 2020. With this in mind, the Montpellier Méditerranée Metropole, the intercommunal administrative structure for the city, initiated a research and development program in 2013.

The program involved several industrial and scientific partners to create a smartphone application to promote sustainable mobility behavior in Montpellier metropolitan area. It funded €2,195,000 on a global budget of €3,225,000 for 30 months starting July 1, 2013. As part of this program, an online survey was conducted to determine the actual mobility behaviors within Montpellier metropolitan area, and recruit testers for the mobile application.

The survey, which ran from June to September 2015, provides information on individuals' mobility behavior within the research area. The database comprises 1,681 commuters. In this study, we have analyzed the data collected on mobility behavior before the implementation of the smartphone application. The study aims to evaluate the impact of travel

[2]We choose the year 2015 because it is the year of data collection for the survey in this study.

[3]The population of these cities are: Paris with 2,148 million of inhabitants; Marseille with 861,635 inhabitants; Lyon with 513,275 inhabitants; and Bordeaux with 249,712 inhabitants.

[4]The fifth tramway line is under construction for about of 15 km of infrastructure and expected to be completed in 2025.

information provision on changes in mobility behavior, covering all information systems regardless of type of source (e.g., website, radio, text messaging, and mobile application).

The remainder of this paper is organized as follows. Section 2 reviews the literature on the impact of information on changes in mobility behavior with a focus on four main impacts: travel and waiting time, transportation mode, route changes, and disrupted scenario. Section 3 presents the methodology, the survey and the data, and the econometric strategy of nested dichotomies is implemented to test the hypotheses inferred from the literature review. Section 4 presents and discusses the results of the study. Section 5 concludes.

2 Literature review: Information and travel behavior changes

This section provides a brief literature review regarding the effects of information on users behavior.[5] Ben Elia and Avineri (2015) define three main types of travel information that influence travel behavior: experiential, descriptive, and prescriptive. According to them, experiential information "is retained in memory and gained by learning reinforced from feedback from past experiences" while descriptive information "includes information describing the prevailing travel conditions, such as current or predicted travel times. It can be provided either before departure (pre-trip) or once on the move (*en-route*). Both can be based on historical or real-time estimates". Finally, prescriptive information "includes a suggestions, guidance, or a recommended alternatives" (Ben Elia and Avineri, 2015, p.1-2). The last two types of information can be provided either before the trip (pre-trip information) or once on the move (*en-route* information), and in real-time as well. Many studies have focused on real-time information (e.g., Tseng et al., 2013; Brakewood et al., 2014; Brakewood and Watkins, 2019; Yu and Gao, 2019), with the increased use of smartphones and associated applications (e.g., Dastjerdi et al., 2019; Khan et al., 2020). Many other types of travel information exist, and we can observe broad trends in the impact of travel information provision on user behavior changes, regardless of the type of travel information provided. For this reason, the literature review on the impact of information provision addresses three major topics: impact on travel and waiting times,

[5]For more exhaustive and comprehensive reviews, see Brakewood and Watkins (2019), Ben Elia and Avineri (2015) and Chorus et al.(2006a).

impact on a mode change, and impact on a route change.

2.1 Impact on travel and waiting times

The main impact of information, mainly the real-time information, is a reduction in current and perceived waiting times and a reduction in overall travel time on public transportation (Brakewood and Watkins, 2019). This decrease in the public transportation travel time ranges from 3% to 45%. For instance, Dziekan and Kottenhoff (2007) showed that the perceived waiting times decreases by 20% after real-time displays were implemented on a tramway line in La Hague, Netherlands; 16 months after installation, the average perceived waiting time decreased from 6.2 minutes to 4.8 minutes. Watkins et al. (2011) and Brakewood et al. (2014) found similar results on perceived waiting times for commuters in Seattle, USA, with the OneBusAway experiment. It is a passenger information system that includes websites, telephones, text messaging, and smartphone applications for the collective transportation network. OneBusAway users have a 30% reduction in perceived waiting time, from 9.9 minutes to 7.5 minutes than users with information received the traditional way. Watkins et al. (2011) also reported that real-time information decreases perceived waiting time by an average of 0.7 minute. Brakewood et al. (2014) found an additional positive consequence of the waiting time reduction. Indeed, these reductions increase the commuters' sense of personal wellbeing and security; the users argue that knowing the waiting times decreases their anxiety and, therefore, increases their safety at a stop.

In another study, Jou et al. (2005) empirically showed that after the provision of real-time information, traffic is more evenly distributed because drivers change their route, which contributes to a decrease in travel time (Ettema and Timmermans, 2006) and could help improve the overall performance of the road network. Improved performance and public transportation user satisfaction also increase with information provision (Brakewood and Watkins, 2019). However, Brakewood and Watkins (2019) warned of a possible bias in the latter outcome of self-reported data with many individuals who always find the information useful. Finally, regardless of the transportation mode (collective or individual), the information provided has a positive impact on decreasing travel and perceived waiting times, which contributes to decreasing the overall travel time because the user waits less time at a station in the collective transportation context. These reductions in travel and waiting times can also be related to changes in departure time. For instance, if an individual waits less time at a station in the context of collective transportation, they changed something in their travel behavior, namely, the departure time. For a private transportation user (e.g., cars), the reduction in travel time can be linked either to a route or a departure time change.[6]

2.2 Impact on a mode change

The main expectation of the information provided is that it will enable individuals to change from car to public transportation or soft modes (e.g., cycling). However, the studies highlighted contrasting results regarding the impact of information on changing travel modes. Chorus et al. (2006b) showed that the impact of information is limited when a user has a general preference for car travel. In a laboratory experiment conducted in Florence, Italy, Innocenti et al. (2013) demonstrated that even if the public transportation network (i.e., metro and bus) is more efficient than a car transportation network, their subjects exhibited strong adherence to the mode choice made during the first round of the experiment. For instance, in the treatment where subjects repeated 50 rounds of choice between car and metro, 71.4% of subjects changed less than 20 times over 50 rounds. They explained this result, in particular, by the high affective value attributed to cars by these users.

According to Steg's (2003) study based in the Netherlands, drivers associate a car with freedom, independence, a status symbol, and the pleasure of driving. Moreover, car users would go so far as to acquire information to reinforce their previous choices (Ben Elia and Avineri, 2015). Farag and Lyons' s survey (2012) conducted in Great Britain (Bristol and Greater-Manchester) in 2007 on 1,327 individuals to induce a mode change confirmed the contrasting results of a mode change with information provision. They studied pre-trip information and concluded that drivers consult pre-trip information less often than those using public transportation. Farag and Lyons (2012) found that individuals' acquisition of information is conditioned by their consideration of using public transportation.

[6]To our knowledge, very few studies have analyzed the relationship between the provision of information and changes in departure times (Caplice and Mahmassani, 1992) as departure times can be confused with route changes.

According to their study, this is not the only factor that affects pre-trip information use; socio-demographic variables, particularly gender, and the social environment too impact pre-trip information use. Additionally, men consult information less than women, and they less prefer cars than public transportation for unfamiliar journeys. When respondents do not know a public transportation user or if nobody advises them, they are less likely to consult pre-trip information.

Nevertheless, pre-trip information is preferred to *en-route* information by users for planning a multimodal trip, and the information required is mainly related to the public transportation segment (Grotenhuis et al., 2007). Kaplan et al. (2017) conducted a parallel study in Brazil and Denmark to provide real-time information on public transportation. They concluded that information quality influences the use of public transport. Information quality explains the perception of the service state; at the same time, familiarity with public transportation influences the transportation system's perceived usefulness and leads to a more frequent use of public transit. Mulley et al. (2017) found small differences between frequent and occasional users of public transit. Therefore, information is a soft factor in mode choice. The result is a complicated relationship between public transportation information and its use.

Finally, the literature review shows that travel information provision has a limited effect on mode change behavior. The shift from car to public transportation is not guaranteed, especially in the short term, as individuals tend to stay with their choice. In the long term, travel information provision could be more important, as individuals would have time to adapt themselves to a new travel behavior through a learning effect (Chorus et al., 2006b).

2.3 Impact on a route change

Even when users who have chosen a transportation mode could make very little use of information to change modes, it could influence other changes in transportation behavior, such as change in routes. Most of the studies on the impact of route choice information involve road routes. The theoretical model developed by Lindsey et al. (2014) on the impact of pre-trip information on route choice showed a correlation between the route conditions considered and the proposed alternative routes. It showed that the information is beneficial when route conditions are uncorrelated, whereas it is harmful when conditions are perfectly correlated. In addition, Chorus et al. (2006a) showed that if travelers' current or planned route performs poorly, then individuals are more receptive to information and, therefore, are more likely to choose a recommended route. This effect is even more substantial if individuals have a fixed expected arrival time – this applies more to business and commuter travel. Abdel-Aty et al. (1994), in their 1992 study in Los Angeles, USA, found that commuters prefer pre-trip information because it allows them to know the situation on their route in advance and, thus, plan a change in route and departure time. This search for information is stronger as traffic conditions are generally poor. The study by Jou (2001) conducted in Taiwan, China, provided interesting results on the main characteristics of individuals who change their route. He shows that commuters who encounter conditions that force them to change (e.g., congestion, accidents) within a week are less likely to change their route often. This result is not in line with Abdel-Aty et al. (1994), who found that variation in traffic conditions positively affects the frequency of route changes. Jou (2001) showed that when a commuter arrives early or late at work, it is more likely to change routes. He also observed that commuters with pre-trip information were more likely to change their routes than those without it.

Furthermore, personal characteristics may influence on route change behavior. Jou (2001) showed that men change routes more often than women do, and young people change routes more often than older people; older people would change routes less often due to habit and risk aversion (Jou et al., 2005). Indeed, risk attitudes play a role in the impact of the provision of information on user behavior. De Palma et al. (2012) specified that individuals with a very high or very low level of risk aversion do not value information and remain poorly informed. Intermediate levels benefit more from this information.

Nevertheless, providing pre-trip information will result in travelers becoming risk-averse (Abdel-Aty et al., 1997). Ben Elia et al. (2013) confirmed this conclusion, concluding that this will result in a preference for more reliable routes (i.e., low variance in travel time). In contrast, risk-seeking individuals prefer unreliable routes with lower average travel times. However, Avineri and Prashker (2006) specified that risk-seeking behavior (i.e., shorter and riskier routes) would be short-term behaviors, and the tendency would disappear in the long term. This trend in risk-seeking behavior is also related to information. Katsikopoulos et al. (2002) determined that the riskier route is preferred during time intervals, that is, the difference between the maximum and minimum travel times, are presented. Ben Elia et al. (2013) pointed out the role played by information accuracy; when accuracy decreases, individuals tend to shift from a risky route to a reliable route, thus confirming a tendency toward risk aversion.

2.4 Impact on disrupted scenario

A last interesting aspect to study is impact of travel information provision on disrupted scenarios. Cats et al. (2011) used a dynamic model, BuzMezzo, to test several scenarios simulating disruptions on the public transport network. The dynamic model is developed for the metro system in Stockholm, Sweden. Cats et al. (2011) proposed two disruption scenarios, a 15-minutes delay and a frequency reduction. They showed that individuals' route choices for stops and lines are influenced by the chosen disruption scenarios, and also by the real-time information available. In disrupted scenarios simulations, the impact of travel information provision is a reduction in travel time (from 9 to 11%), and in waiting time up to 18%. In addition, providing real-time information can have impacts to reduce vulnerability on public transportation network (Cats and Jenelius, 2018). For instance, Kattan et al. (2011) found that 21.4% of highway users reported changing to variable message sign-suggested routes in the event of an accident or construction, and 16% reported changing occasionally.

To summarize the literature review, the provision of information has a limited impact on travel behavior changes (i.e., mode, route, or departure time changes). Individuals will have strong habits mainly for commuting trips (Farag and Lyons, 2012; Chorus et al., 2006b; Ben Elia and Avineri, 2015), while information will have a more significant impact on non-usual trips (Emmerink et al., 1996; Chorus et al., 2006b; Farag and Lyons, 2012; Horold et al., 2015). For instance, Kaplan et al. (2017) showed that real-time information searches are associated with night trips and unfamiliar journeys. When individuals are unfamiliar with a place, they spend more time searching for information (Horold et al., 2015). Essen et al. (2016) also indicated that as long as individuals are satisfied, they will not pay attention to information to reduce their cognitive efforts. Thus, if commuters have already experienced problematic situations such as congestion or travel time variability, they are more likely to change their travel behavior (Chorus et al., 2006b). An issue remains about the levels of situations that would lead commuters to change their behavior. In addition to the trip definition of a trip, several socio-demographic characteristics define trips as well as trip information users. They are generally men with high education levels, high incomes (Abdel Aty et al., 1994), and mobile phones (Chorus et al., 2006b; Khan et al., 2020). However, this typical profile does not necessarily imply that they will change their travel behavior most because of this information.

3 Methodology

An empirical strategy based on a questionnaire survey was implemented to answer the research question of evaluating the impact of information on changes in transportation behavior. Section 3.1 discusses the questionnaire structure and the data collection process. Section 3.2 establishes assumptions to be tested using the data collected on a convenient sample of Montpellier metropolitan area commuters, and Section 3.3 presents the econometric strategy to model the impact of travel information provision on behavioral changes.

3.1 Survey and data collection

3.1.1 Questionnaire structure

The questionnaire included 74 items and is divided into 4 parts. The first part collected the respondents' main socio-demographic characteristics: age, gender, occupational category, household size, number of children, residential location, and workplace. The second focused on respondents' travel habits: car ownership, public transportation pass, choice of transportation modes for commuting, number of modes used, travel schedules, and perceived travel cost. The third part was devoted to travel information using by respondents: the use of pre-trip and *en-route* information sources, the number of sources used, reliability and trust in the information provided, and behavioral changes induced. The fourth part addressed local transportation issues:3M area inhabitants' perceptions of congestion, noise, air pollution, parking problems, bicycling and walking issues. The last part was not used in this study.

3.1.2 Data collection process

A large-scale survey was conducted among the Montpellier metropolitan area inhabitants as part of a more general project on multimodal transportation and mobility topics to better understand travel behavior.[7] The data collection process was implemented via an online survey from June 16, 2015, to September 7, 2015. The online questionnaire was sent using various email mailing lists (e.g., Montpellier metropolitan area, University of Montpellier, business, and private networks), and other communication media. Due to participative and inclusive citizenship considerations, no inclusion criteria were used. We obtained 2,310 responses. After checking and cleaning the questionnaires of missing data and some conditions (e.g., only commuters were targeted), we obtained a convenient sample of 1,681 commuters.

3.2 Assumptions to be tested

Five hypotheses were defined based on a literature review on the impact of travel information on mobility behavior changes. They were tested using the data collected on commuters in research region. The hypotheses are as follows:

- **H1:** Young, educated men search for information more often and, therefore, will change their travel behavior.

The literature review highlighted a typical individual profile that is more sensitive to search for travel information and use it to change travel behavior (e.g., Jou, 2001; Jou et al., 2005). They showed men and young people change route more often than women and older people. We tested if this same individual profile of young, educated men would appear in the Montpellier metropolitan area.

[7] Montpellier metropolitan area comprises 31 towns covering a surface area of 421.8 km^2, with 465,070 inhabitants (2016), more than half of whom live in Montpellier (i.e., 285,121). The city of Montpellier attracts many commuters due to numerous employment opportunities. Still, considering Montpellier's small size, its rank of being the third most congested city in France is the most singular.

- **H2:** Commuters with a public transportation pass search for more information and, therefore, will change their travel behavior.

The aim is to verify the impact that a public transportation pass can have on mobility behavior changes. Public transportation commuters were assumed to have such a pass and to be seeking more travel information because they are dependent on buses and tramways. Some of it is received automatically, such as online displays at stations without even looking for information. Thus, these commuters should adapt their mobility behavior more often by changing their schedules, routes, or even travel modes (Cats et al., 2011).

- **H3:** The more commuters use many pre-trip information sources, the more they will change their travel behavior.

According to the literature, individuals prefer pre-trip information when planning their trips, especially when a trip part is made by public transportation (e.g., Mulley et al., 2017). In a private transportation context, the pre-trip information allows us to know the traffic state in advance; therefore, users can change or adjust their route and departure time. In addition, commuters have many pre-trip information such as websites, mobile applications, listening radio, and variable message signs. All travel information sources are grouped under the name of advanced travel information systems. Therefore, we assumed that a commuter using an increasing number of pre-trip information sources would encourage a change in his travel behavior.

- **H4:** Commuters with high travel times would use more travel information and, therefore, change their travel behavior.

The literature review highlights that provision of travel information contributes to decreasing the overall travel time of individuals (e.g., Brakewood and Watkins, 2019; Cats et al., 2011; Ettemma and Timmermans, 2006). Thus, logically, individuals with higher travel times will be more willing to seek information and ultimately adjust their travel behavior.

- **H5:** Commuters with a positive safety margin would use more travel information and, therefore, change their travel behavior.

Safety margin (Knight, 1974) defined the additional travel time an individual integrates with the total travel time to cope with the negative consequences of uncertain travel times. It can be measured as the difference between the individual expected travel time and the actual travel time using the schedules predicted by an individual, and the average travel time:

$$\text{SM} = t_w - t_h - E(t), \tag{1}$$

where t_w is the preferred arrival time from activity (e.g., work), t_h is the departure time from home, and $E(t)$ is the average (or expected) travel time for the trip. From Equation (1), three cases can be obtained. First, individuals with a negative safety margin ($\text{SM} < 0$) imply that they do not plan enough time to allow them to be on time. Second, individuals with a zero safety margin ($\text{SM} = 0$) imply that they plan just enough time to be on time. Third, individuals with a positive safety margin ($\text{SM} > 0$) imply that they plan additional time to protect themselves from uncertainty.

According to this definition, a safety margin can be viewed as a proxy for prudent behavior.[8] In the same vein as De Palma et al. (2012), we assumed that prudent individuals characterized by a positive safety margin would be more willing to search for information and use it to change their travel behavior.

3.3 Overview of the econometric strategy

Assessing the role of traveler information provision on changing mobility behavior requires modeling users' decision-making processes and identifying their main determi-

[8]For economists, risk aversion refers to the fact that individuals dislike any risky situation, while prudence refers to the way in which they will protect themselves against that risk.

nants. The questionnaire was designed to identify three specific kinds of behavior regarding the impact of travel information provision on mobility behavior. This was done by employing a series of questions. The first observable behavior is due to individuals who do not use any information sources (pre-trip or *en-route*) for their commuting trips. Another type of behavior is that of individuals who search for travel information provision but do not use it to adjust or modify their mobility behavior. The last type of behavior concerns individuals who use the provision of travel information to adjust or modify their mobility behavior.

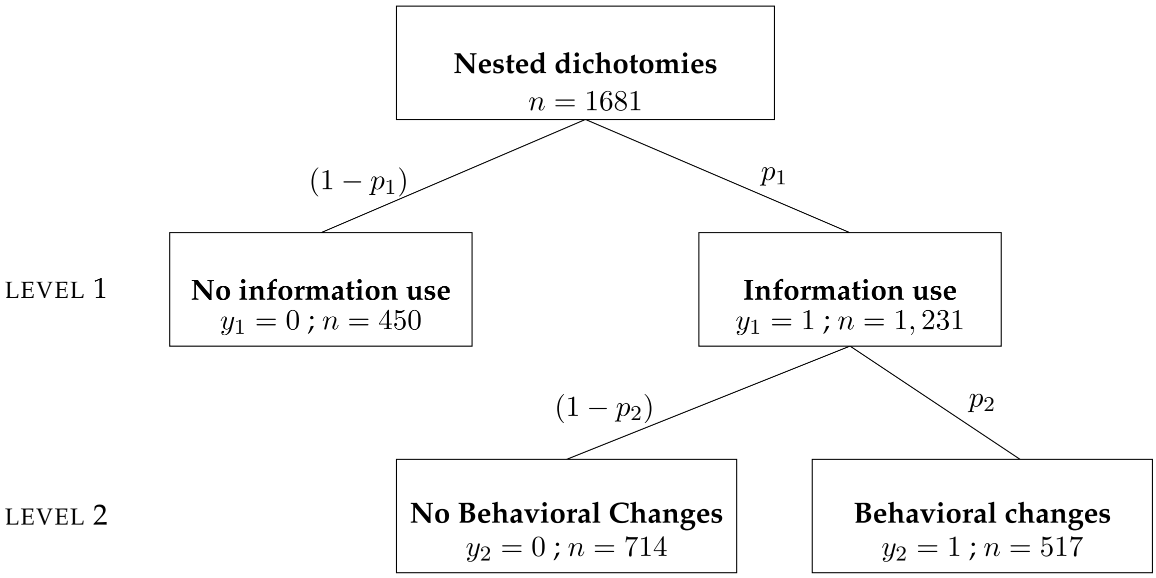
A categorical variable was built with three mutually exclusive categories, one for each type of behavior. The objective was to model the probability that a given individual in our sample will adopt one of the three behaviors identified above.

We opted for the nested dichotomies method (Fox, 2016; Friendly and Meyer, 2015).[9] This method separates the three alternatives of the categorical variable into two dichotomies, each estimated using a binary logit model. As Fox (2016) pointed out, this method is reasonable if dichotomies' choices are not arbitrary. The nested set of two dichotomies appears to be well founded. At the first level, we distinguished between individuals who do not use any information sources and those who use travel information provision. At the second level, we studied whether the travel information provision impacts users' mobility behavior only for individuals who used travel information sources. The nested dichotomies are shown in Figure 1.

Indeed, the decision-making process can be considered sequential. At the first level, commuters decide whether to use a travel information source for their Montpellier metropolitan area trips. At the second level, if they have chosen to use an information source in the first step, commuters decide whether to use the information provided to change or adjust their mobility behavior.

At each level, we modelled the choice between the two alternatives using a binary logit. As demonstrated by Friendly and Meyer (2015) and Fox (2016), each dichotomy is in-

[9] We first employed a generalized logit model to estimate this probability, but the Small and Hsiao test (1985) rejected the null hypothesis of the independence of irrelevant alternatives. We then turned to a multinomial probit model, which implicitly assumes the homogeneity of slopes for each utility function associated with the alternatives considered. Since the slope homogeneity test was rejected, we finally opted for the method of nested dichotomies.



Note: n is the number of individuals for each decision.

Figure 1: Nested dichotomies structure

dependent. Consequently, the probability of a given alternative or option is simply the product of the probability obtained at each level, provided that the given alternative exists at the level under consideration. For instance, we determined the probability of using travel information as Prob(Use)= p_1, and the probability of using the travel information but not changing behavior as Prob(Use and No change)= $(p_1) \times (1 - p_2)$. Then, we calculated the probability of using travel information and change in behavior as Prob(Use and Change)= $(p_1) \times (p_2)$.

As we used a binary logit at each level, these probabilities can be written as:

$$(\text{Level } 1) \qquad \mathrm{Prob}(\text{Use}) = p_1 = \frac{e^{Z_1}}{1 + e^{Z_1}} \tag{2}$$

where $Z_1 = X\beta_1 + \epsilon_1$, with X is the vector of explanatory variables,[10] β_1 is the vector of coefficients to be estimated, and ϵ_1 is the random term distributed according to Gumbel's distribution.

$$(\text{Level } 2) \qquad \mathrm{Prob}(\text{Change}) = p_2 = \frac{e^{Z_2}}{1 + e^{Z_2}} \tag{3}$$

where $Z_2 = X\beta_2 + \epsilon_2$, with X is the vector of explanatory variables, β_2 is the vector of

[10]The potential explanatory variables are various and numerous. They are listed and described in detail in Table 1 of the Section 4.

coefficients to be estimated, and ϵ_2 is the random term distributed according to Gumbel's distribution.

$$\text{Prob(Use and Change)} = (p_1) \times (p_2) = \frac{e^{Z_1} \times e^{Z_2}}{(1 + e^{Z_1})(1 + e^{Z_2})} \tag{4}$$

$$\text{Prob(Use and No Change)} = (p_1) \times (1 - p_2) = \frac{e^{Z_1}}{(1 + e^{Z_1})(1 + e^{Z_2})} \tag{5}$$

The probability defined by Equation 4 allows us to explore the determinants of this change. The estimation strategy described in Figure 1 was used, and the main results are presented in Section 4.

4 Results

4.1 Descriptive statistics

Before discussing the econometric results, we proceed to an analysis of the data using descriptive statistics. Table 1 shows the socio-demographic characteristics of the respondents (1,681) and their commuting habits.

While no inclusion criteria were defined, because of the keenness of local public authorities to involve all citizens (an inclusive, participative, and collaborative survey), the sample is gender balanced and consistent with the INSEE study results (2013) on Montpellier metropolitan area inhabitants,[11] according to Pearson's chi-square test.[12]

The respondents were quite young, with more than two-thirds of them being 18–39 years old, and only 3% of them are 60–75 years old. Moreover, the main occupational categories of respondents were students (33.4%), managerial staff (30%), and employees (24%). Respondents between 18 and 39 years old and managerial staff were over-represented in the data.[13] We obtained rather small households with an average of 1.61 consumption units

[11] INSEE, recensement de la population 2013, projections de population (modèle Omphale 2017), https://www.insee.fr/fr/statistiques/3673373#tableau-figure3

[12] See Supplementary Materials, Tables 1 to 3.

[13] This over-representation may have an impact on the validation of **H1**. Indeed, since our sample is not representative of the Montpellier metropolitan area population, and since the two categories based on **H1** are over-represented, this hypothesis could be verified by default. Consequently, we will have to be cautious in the analysis of this hypothesis.

per household.[14] This also reflects the overall inhabitants of Montpellier metropolitan area (1.68).

Table 1: Sample characteristics on socio–demographic traits and commuting habits

Variables	Freq.	Percent.	[INSEE, 2013]	Variables	Freq.	Percent.
Gender				**Transportation mode used**[1]		
Male	826	49%	[48%]	Private vehicle (*i.e.*, car, motorbike)	736	44%
Female	855	51%	[52%]	Carpool	52	3 %
				Tramway	883	53%
Age				Bus	399	24%
18 to 39 years	1,185	70%	[49%]	Railways	54	3%
40 to 59 years	453	27%	[32%]	Bicycle	452	27%
60 to 75 years	43	3%	[18%]	Walking	463	28%
				Others (*e.g.*, scooter)	19	1%
Occupational category				**Multimodal Transport**		
Farmer	3	0.18%	[0.11%]	Yes	501	29.3%
Craft person	64	3.81%	[3.08%]	Sometimes	240	14.28%
Worker	11	0.65%	[6.59%]	No	935	56.42%
Employee	400	23.8%	[12.73%]	**Car ownership**		
Middle staff	123	7.31%	[13.29%]	Yes	1,121	67%
Managerial staff	512	30.46%	[10.36%]	No	560	33%
Student	568	33.79%	[36.43%]	**Public transportation pass**		
				Yes	745	44%
Household structure (mean)				No	936	56%
Adults		1.98		**Shopping after work**		
Children		0.40		Yes	976	58%
Consumption Units		1.61	[1.68]	No	705	42%
				Commuting characteristics (mean)		
				Number of vehicles owned		1.23
				Perceived cost (€)		3.39
				Travel time (min)		28.83 mins
				Safety margin (min)		7.82 mins

[1] The question on transportation mode used allowed for multiple answers, so the sum of percentage of all transportation modes used may exceed 100%.

As for the respondent's commuting habits (Table 1, right side), a majority of respondents, or 80%, used public transportation (i.e., tramway, bus, or railways) , and 55% used active transportation modes (i.e., bicycle and walking). Only 44% reported using a private vehicle (e.g., car, motorbike) to commute for all or part of their trips. Moreover, about one-third of the respondents combined several transportation modes always, while 14% did so sometimes, and 56% were exclusive users of only one transportation mode. Two-thirds of the respondents (67%) owned at least one car in the household. Finally, 44% had a public transportation pass.

[14] Consumption units (CU) is a weighting system used by the French National Institute of Statistics and Economics Studies (INSEE). The first adult of the household has a weight of 1.0; any additional person older than 14 years has a 0.5 weight while any additional person younger than 14 years has a 0.3 weight.

From the survey responses, the one-way average commuting characteristics were calculated. On average, the perceived cost of commuting for one-way was estimated to be at around €3.39. The average travel time for commuting (one-way) was estimated to be 29 minutes, with an average safety margin of approximately 8 minutes. This implied that an individual allocated an extra 8 minutes as a precaution against a travel disruption or congestion for a 29-minutes trip (i.e., 27.1% of additional travel time precisely with the figures provided in Table 1). These figures are quite consistent with those provided by the 2015 Traffic Index Ranking (by TomTom®), which estimated a 28% additional travel time for commuting trips due to traffic jams in Montpellier.

Table 2 provides some elements of travel information used by the respondents. First, 73% of respondents reported using travel information sources (e.g., mobile applications, radio, text messaging). Nevertheless, pre-trip information is used more often than *en-route* information. Only 31% of respondents reported never using pre-trip information, while 48% reported never using *en-route* information. This assessment is consistent with Grotenhuis et al. (2007), who explained that pre-trip information is preferred to users' *en-route* information.

The provision of information through websites and mobile applications is dominant among all the travel information sources used. The questionnaire differentiates between websites and mobile applications. At the time of the survey, the public transportation operator, *Transport de l'agglomération de Montpellier* (TaM) did not have an official mobile application. A traveler who wanted to obtain official information had to go to the TAM website. However, unofficial mobile applications have been developed in parallel, along with Facebook and Twitter groups, to share travel information such as network disruptions and inspector attendance.

Finally, although 73% of respondents reported using an information source, only 31% reported using it to change their travel behaviors. Travel behaviors take into account changes in transportation mode as well as in route or changes in departure times. Unfortunately, the survey was not designed to directly identify one of the three behavioral changes. This is a limitation of the study, even if some insightful elements of the type of change involved can be deduced indirectly.

Table 2: Sample characteristics on pre-trip and *en-route* information uses

Variables	Freq.	Percent.	Variables	Freq.	Percent.
Using any information source					
Yes	1,231	73%			
No	450	27%			
Using pre-trip information source			**Using *en-route* information source**		
Always	147	9%	Always	101	6%
Often	441	26%	Often	290	17%
Sometimes	577	34%	Sometimes	492	29%
Never	516	31%	Never	798	48%
Types of pre-trip information sources			**Types of *en-route* information source**		
Internet websites	880	52%	Internet websites	467	28%
Smartphone applications	518	31%	Smartphone applications	492	29%
Radio	140	8%	Radio	154	9%
Text-messaging	15	0.9%	Text-messaging	13	0.77%
Others (*e.g.*, GPS)	31	1.8%	Others (*e.g.*, GPS, schedule display)	59	3.5%
Using the information provided to change travel behavior					
Yes	517	31%			
No	1,164	69%			

To check the existing relationships between variables, contingency tables and χ^2 tests were carried out; all the tables have been grouped together in the supplementary material documents. This analysis allowed for commenting on the hypotheses defined in Section 3.2.

The study found a relationship between the age of commuters and their information use and frequency of change in mobility behavior. It appears that there were issues of over- and under-representation of the 40–59 age group. Specifically, it was over-represented in the non-use of travel information and occasionally in changing mobility behavior. At the same time, this age group was under-represented in using information and changing mobility behavior often and always. In contrast, there was no relationship between the education level captured by the occupational category and information use or mobility behavior change. Thus, H1 was unlikely to be verified, or only partially verified, because there was no relationship between information use and mobility behavior change as well as education level and mobility behavior change. This was only affected by age. Econometric modeling should shed additional light on the validation of H1.

H2 dealt with the relationship between use of travel information and commuters with a public transportation pass. Based on χ^2 tests on supplementary material documents, there was indeed a relationship between travel information use and ownership of a public transportation pass and the frequency of mobility behavior change. Nevertheless, the test pointed to two problems. The first was the under-representation of commuters who did not have a public transportation pass and who always changed their mobility behavior.[15] The second was the problem of over-representing commuters who had a public transportation pass, and who always changed their mobility behavior.[16]

The χ^2 tests showed a relationship between the frequency of information use (both pre-trip and *en-route*) and the frequency of mobility behavior change, which was in line with H3. The econometric results will allow us to go further in terms of the importance of the different factors and confirm or invalidate the hypotheses defined in Section 3.2.

4.2 Econometric results

4.2.1 General considerations

The econometric strategy defined in Section 3.3 and Figure 1 is applied, and the results are provided in Table 3 for each level of the dichotomies nested structure. At each level, we introduced explanatory variables linked to socio-demographic characteristics and commuting habits (Table 1) and linked them to pre-trip and *en-route* information use (Table 2). Only variables that were significant at least at the 10% level, were included in the model.[17]

The likelihood ratio tests showed that the models were valid at both the first and second levels. The proportion predicted with success was quite good at 67% and 70% respectively, at the first and second levels. The goodness of fit was satisfactory, with an overall $Pseudo - R^2$ of 0.117. It should also be noted that there were no common explanatory variables at each level, which justifies the analysis of the level 1 and level 2 models separately. Only when we attempt to assess the global impact on the probabilities expressed by Equations (2), (3), and (4) of the set of variables will we use the Level 1 and Level 2 variables simultaneously.

[15] See supplementary material, Table 9: Contingency table between public transportation pass and frequency of mobility behavior change with Pearson's chi-squared test.

[16] See supplementary material, Table 9: Contingency table between public transportation pass and frequency of mobility behavior change with Pearson's chi-squared test.

[17] For qualitative variables, we used Type 3 effects analysis to determine whether the variable should be kept. If so, this means that the variable had a significant effect on the explained probability, even if this cannot be true for all the categories (e.g., the age variable).

Table 3: Nested dichotomies estimation

	Level 1		Level 2	
Dependent Variables	Information Use ($y_1 = 1$)		Behavioral Changes ($y_2 = 1$)	
Explanatory Variables	**Coef.**	**p-value**	**Coef.**	**p-value**
Intercept	0.8614	<0.0001	-3.0144	<0.0001
Age				
18 to 39 years	*Ref.*	*Ref.*	–	–
40 to 59 years	-0.5087	<0.0001	–	–
60 to 75 years	0.2504	0.5145	–	–
Public transportation pass				
No	*Ref.*	*Ref.*	–	–
Yes	0.4259	0.0003	–	–
Shopping after work				
No	*Ref.*	*Ref.*	–	–
Yes	0.2891	0.0119	–	–
Car ownership				
Yes	–	–	*Ref.*	*Ref.*
No	–	–	0.5341	0.0015
Commuting by car				
No	–	–	*Ref.*	*Ref.*
Yes	–	–	0.4989	0.0025
Travel time	–	–	0.0127	<0.0001
Safety margin	–	–	0.0258	0.0079
Square of safety margin	–	–	-0.00031	0.0681
Number of *en-route* information sources used	–	–	1.8165	<0.0001
Number of Observations	1,681		1,231	
Likelihood Ratio Test	42.86	<0.0001	378.81	<0.0001
Proportion Predicted with Success	67%		70%	
Overall $Pseudo - R^2$	0.117			

4.2.2 Level 1: Determinants of travel information use

In the sample, 450 individuals reported that they did not use information sources for commuting trips within the research region. At the same time, 1,231 commuters reported using pre-trip or *en-route* information sources. At level 1, the probability of using pre-trip or *en-route* information sources was modeled (i.e., $y_1 = 1$ in Figure 1). Three variables — the individual's age, owning a public transportation pass, and declaring to shop after work — had a significant impact on the probability of using pre-trip or *en-route* information sources.

The age variable, belonging to the 40–59 years group, reduced the probability of using a pre-trip or *en-route* information sources compared to the reference category (18–39 years).[18] This seems quite logical because young people are more comfortable with digital innovations and applications available on smartphones. Since no gender or educa-

[18]No comment on the 60-75 years group can be made due to its non-significant coefficient.

tional effects could be demonstrated by econometric modeling, H1 is only very partially validated.

In addition, owning a public transportation pass undoubtedly positively impacted on the probability of using information sources. Indeed, with a positive and significant coefficient of this variable in the econometric modeling, we retrieved widely documented results in the literature (Farag and Lyons, 2012; Grotenhuis et al., 2007). The travel information provision allowed this category of individuals to optimize their transportation chain and avoid or diminish the breaking loads. This result confirmed the first part of H2 that commuters with a transportation public pass use more travel information.

Finally, the last determinant identified by the model as having an impact on the probability of using an information source was related to the fact that an individual plans to shop after work. In such circumstances, which can put individuals out of their daily routine, it makes sense for them to use pre-trip or *en-route* information sources. In an uncertain context, the use of an information source is of interest to individuals, as it diminishes stress and increases personal security. Other studies have confirmed this, including Brakewood et al. (2014), and Brakewood and Watkins (2019). What requires consideration is if the use of this information by commuters helps them modify or adjust their mobility behavior.

4.2.3 Level 2: Determinants of mobility behavior changes

Of the 1,231 respondents who reported using an information source for their commuting trips, only 517 commuters (i.e., 41.99%) reported using the information provided to modify or adjust their mobility behavior. At level 2, the probability of changing mobility behavior due to travel information provision is modeled (i.e., $y_2 = 1$ in Figure 1). The econometric results are listed in Table 3.

Econometric modeling showed that the five variables have an impact on the previous probability; two were qualitative, and three were quantitative. The qualitative variables that had an impact on the probability of changing mobility behavior were whether one owned a car and whether one made commuting trips by car. The econometric modeling highlighted the quantitative variables impacting this same probability, travel time, safety margin and its square, and the number of *en-route* information sources used.

According to our model results, not owning a car would increase the probability of using the information provided to adjust or modify mobility behavior. This seems fairly credible because an individual in such a situation must use either public transportation (e.g., bus or tram), shared modes (e.g., carpooling, carsharing, bike-sharing), or active modes (e.g., cycling, walking). Therefore, this mobility must be organized and requires the use of travel information and adaptation of mobility behavior. For this type of individual, changes in behavior may, therefore, may be linked to changes in transportation modes, routes, or departure times.

Another interesting finding was in line with the transportation mode chosen for daily commuting within the research region. Traveling by car allowed greater flexibility in schedule and route choices than traveling by public transportation. Thus, using cars for such trips would increase the probability of changing mobility behavior due to the travel information of various sources. In this case, the aim of changing mobility behavior would be to optimize travel time by avoiding heavily congested sectors or routes, or possibly by changing departure times. This would, therefore, help to make cars more efficient. These results were fully consistent with the theoretical prescriptions of the model developed by Lindsey et al. (2014), with the numerical simulations by Ettema and Timmermans (2006) as well as the empirical findings of Jou et al. (2005).

Travel time played an unambiguous role in the probability of changing mobility behavior owing to the travel information provided. This impact was positive, which meant that the more the travel time, the more the user would try to optimize it by using the information provided and changing behavior. Therefore, this was in line with the validation of H4.

The safety margin — which can be seen as an operational measure of the prudence concept in a risky decision context — also played an important role in the probability of changing mobility behavior as a result of the travel information provided. Nevertheless, and contrary to the travel time variable, safety margin intervened in econometric modeling through not only a linear but also a quadratic term. This specific feature meant that safety margin had a non-monotonic impact on the studied probability and revealed the existence of a threshold effect: an increase in the safety margin until 41.6 minutes increased this probability and decreased the probability beyond this level. Consequently, a prudent individual with a low safety margin ($0 < \textsc{sm} < 41.6$ min) has a growing probability of using the travel information provided to change their mobility behavior.[19] Therefore, this was in line with the validation of H5.

The results obtained concerning the impact of travel time and the safety margin on the probability of changing mobility behaviors due to information provision fully validated H4 and H5. To the best of our knowledge, this result has not been documented in the economic literature on transportation.

Finally, at level 2, the number of *en-route* information sources used appeared to be one of the determinants of mobility behavior change. With a positive coefficient associated with this variable, it meant that the more individuals consulted *en-route* information sources, the more likely they were to use the information to adjust or modify their mobility behavior. This result was consistent with the validation of H3. Moreover, the econometric modeling used did not reveal users' preference for pre-trip information sources, as it is usually documented in the literature, and more specifically in the studies conducted by Abdel-Aty et al. (1994) and Grotenhuis et al. (2007). This finding invalidated H3.

We will now pool the explanations obtained at the two levels to compute the probability established in Equation (4) and discuss its sensitivity in Section 4.3.

4.3 Discussion

Faced with the numerous negative externalities of urban trips, local public authorities have to design and implement policies to promote sustainable urban mobility. In France, to achieve this goal, local public authorities initially chose to invest in heavy public transportation infrastructure networks by redeploying the tramway in the early 2000s and reducing the space devoted to cars. The policy aimed to achieve a modal shift from the car to public transportation but achieved its objective only partially, given the density of public transportation in Montpellier metropolitan area. With the rise of digital technologies, local public authorities have placed their hope on connected and shared mobility (real-time information for users and multimodal approach).

Our study aimed to assess the power of travel information provision on users' behavioral changes in mobility. Some determinants of both aspects (use of information and

[19] These results will be further explored inSection 4.3.

behavioral changes) have been previously identified, and we now focus on the probability defined in Equation (4) and its sensitivity. More specifically, we provided some insights into the variations in the probability that an individual will use an information source and change his/her mobility behavior.[20] To assess the variations in the previous probability, we distinguished between the quantitative and qualitative variables. For the former, we computed the probability's elasticity, and for the latter, we computed the relative variation in the probability. The results are provided in Table 4 and supplemented by graphs (see Figures 2 and 3).

Table 4: Variation of Prob(Use and Change)

At this average point, Prob**(Use and Change)** = 0.308			
	Sensitivity		***Elasticity***
Age			
18 to 39 years	**0.324**	**Travel Time**	+0.25
40 to 59 years	-20.06%	(29 minutes)	
Public transportation pass			
No	**0.287**	**Safety margin**	+0.11
Yes	+16.17%	(8 minutes)	
Shopping after work			
No	**0.286**	**Number of *en–route***	+1.17
Yes	+18.44%	**information sources used**	
Car ownership			
Yes	**0.295**		
No	+12.91%		
Commuting by car			
No	**0.292**		
Yes	+14.66%		

Notes : In bold is the probability; the other figures describe the evolution of the probabilities for any categories other than the reference category, all things being equal.

These graphs were built to provide illustrations of the impact of the various variables, identified at levels 1 and 2, on the probability that individuals will use the information provided to modify their mobility behavior. To do so, the graphs describe the impact on the previous probability of travel time on the one hand (left–hand graphs in Figures 2 and 3) and the safety margin (right–hand graphs in Figures 2 and 3). In addition, the

[20]We have made the computations at the average point of our sample. This point is defined by the following characteristics: Age = '18–39', Public Transportation Pass = 'No', Shopping after Work ='No', Car ownership = 'Yes', Commuting by car = 'No', Travel Time = 29 mins, Safety Margin = 8 mins, Number of *en-route* information sources used = 1.

probability evolution curves were plotted for the different categories of the qualitative variables identified as having a significant role.

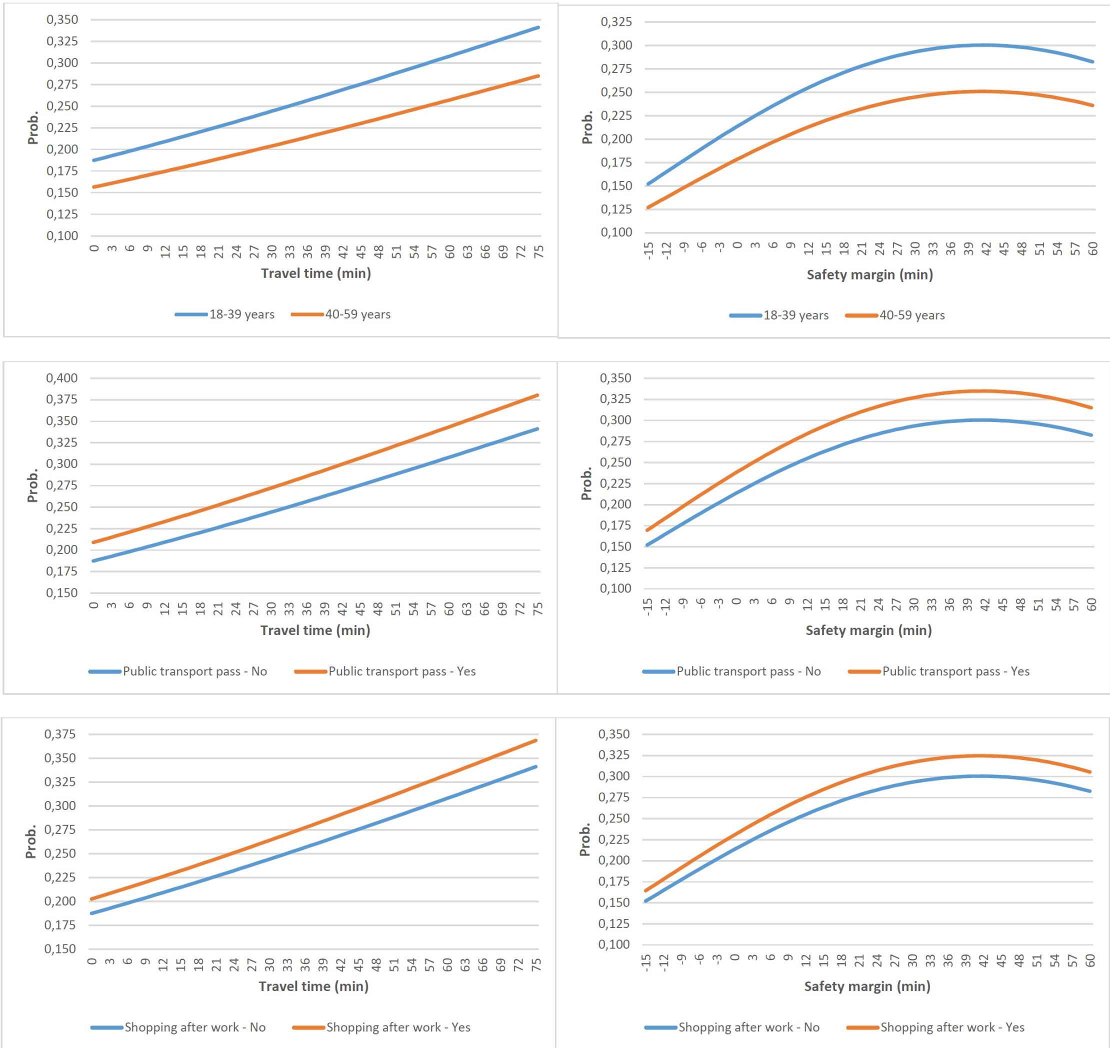


Figure 2: Impact of the various determinants on the Prob(Use and Change) (Part I)

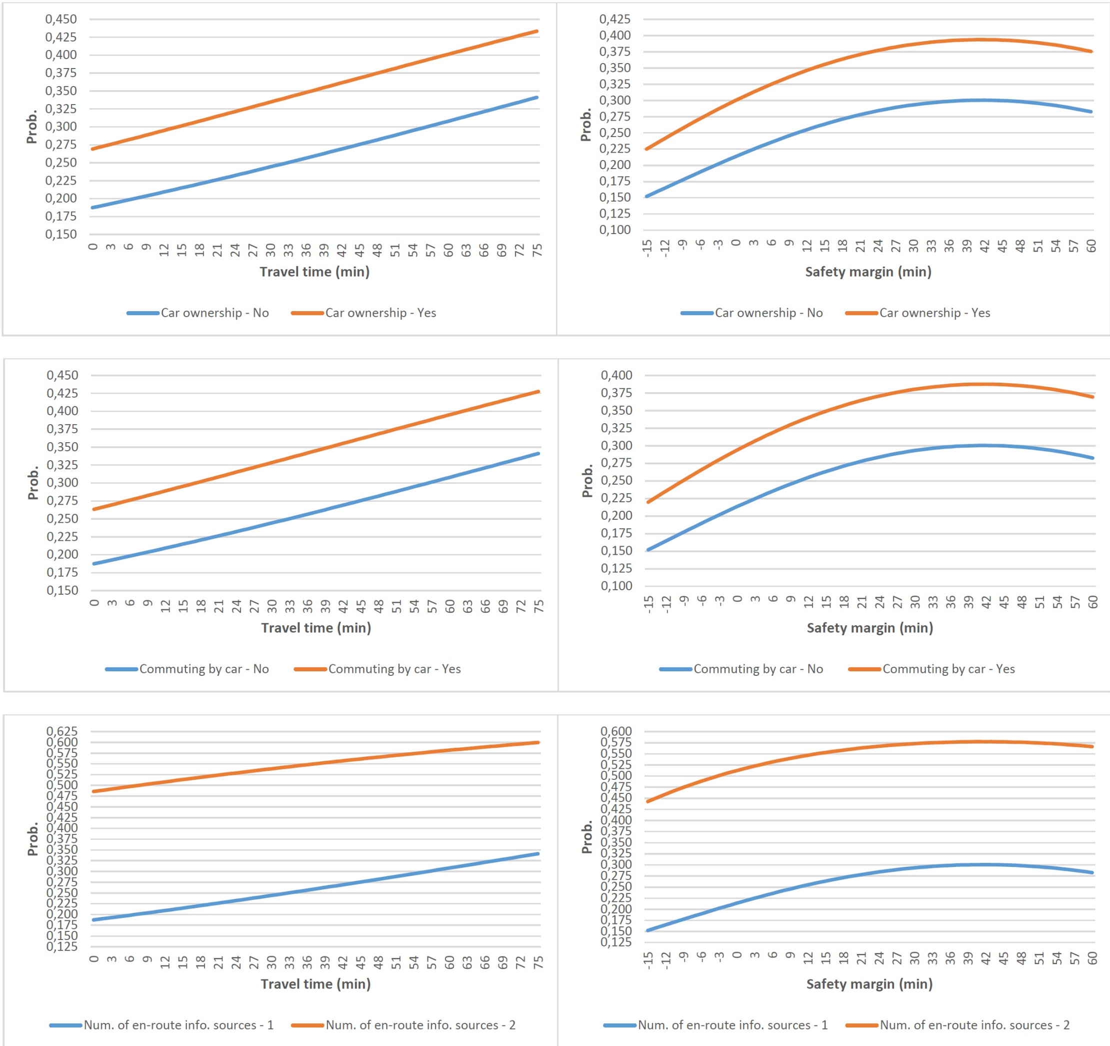


Figure 3: Impact of the various determinants on the Prob(Use and Change) (Part II)

We focused our comments primarily on the discussion and validation of H4 and H5 since the relationships established therein have been relatively untested in previous studies.

Travel time had a positive and linear effect on the probability that an individual would use travel information to change their mobility behavior. All other things being equal, this probability was all the greater when the individual owned a car (+12.91%), commuted by car (+14.66%), used several *en-route* information sources (elasticity of +1.17), and for young people (-20.06% for 40 to 59 years compared to 18 to 39 years). The determinants at level 2 seemed to significantly influence the probability (both on level and difference base) than the determinants identified at level 1 of the nested dichotomies structure.

As noted earlier, the safety margin had a non-linear effect on the probability that an individual would use the travel information provided to adjust their mobility behavior. This non-linearity revealed the existence of a threshold effect (41.6 min): before this threshold, the probability increased; after this threshold, it decreased. Again, the variables of level 2 seemed to have a greater influence on the previous probability than those of level 1. The study's findings on the impact of travel time on Prob(Use and Change) remained valid in the context of the safety margin studies.

However, additional results can be obtained. Indeed, three types of individuals can be distinguished depending on the value and the magnitude of their safety margin:

- ***Chronic non–prudent individuals***. With a negative safety margin (-15 min $\leq SM <$ 0 min), these individuals do not correctly anticipate recurrent congestion or disruption and have a low preference for punctuality. Logically, for these individuals, the probability of using the travel information provided to change their mobility behavior is relatively low (about 0.150) but tends to increase for individuals with a safety margin close to 0 min (about 0.225).

- ***Reasonably prudent individuals***. With a positive safety margin (0 min $\leq SM <$ 41.6 min), these individuals make full use of the travel information provided and adapt their mobility behavior accordingly. For these individuals, the probability Prob(Use and Change) varied from 0.225 to 0.575.

- ***Excessively prudent individuals***. With a positive and large safety margin ($SM \geq$ 41.6 min), these individuals have such a large precautionary margin that they tend to make less use of provided travel information to change their mobility behavior. Therefore, it is quite logical that the probability Prob(Use and Change) decreases as the individuals' safety margin increases (from 0.575 to 0.275).

These results can be linked to those of De Palma et al.'s (2012) analysis of risk aversion and information value. These authors showed that risk-neutral or low-risk averse individuals were the main beneficiaries of information. In contrast, individuals at extreme bounds (i.e., with very high-risk aversion or very low-risk aversion) remained misinformed and therefore did not change their behavior. We retrieved the same kind of results for prudence attitudes as his for risk aversion. Indeed, our results established that chronic non-prudent individuals, and excessively prudent individuals would make less use of information and change their behavior less than reasonably prudent ones.

5 Conclusion

This study on the Montpellier metropolitan area aimed to assess the role of travel information provision on behavioral changes for commuters. Based on the literature review, we established five assumptions regarding the expected effects of travel information provision on behavioral changes in commuters. We tested these five assumptions on a convenient sample of 1,681 commuters in Montpellier metropolitan area collected during the summer of 2015. The main results are summarized below.

No gender and educational effect could be highlighted in our study, while being young had an impact. However, we remain cautious about the results' true scope since we had an over-representation of the young age group (18–39 years old). These findings would therefore contribute to a very partial validation of H1 – *Young, educated men search for information more often and, therefore will change their travel behavior*. Moreover, having a public transportation pass positively influenced the probability of users using travel information for commuting trips. This result was in line with H2 – *Commuters with a public transportation pass search for more information and, therefore, will change their mobility behavior*. Furthermore, contrary to what was generally documented in the literature, our results showed that 3M commuters were more sensitive to *en-route* information and used it to modify or adapt their mobility behavior, which would invalidate H3 – *The more commuters use many pre-trip information sources, the more they will change their travel behavior*.

Undoubtedly, travel time had a positive impact on the probability of changing mobility behavior due to travel information use. The longer the travel time, the more commuters tried to optimize it by using information and changing mobility behavior. H4 – *Commuters with high travel time would use more travel information and, therefore will change their travel behavior*, was therefore verified for our commuter sample. This result was not really surprising, even though the role played by this factor was rarely highlighted in the literature.

The last assumption we wanted to test in this study is the impact of commuters' prudence on travel information use. As an operational measure of the prudence concept, the safety margin allowed us to highlight a threshold effect and characterize commuter profiles according to their prudence levels. First, chronic non-prudent individuals were characterized by a negative safety margin. These individuals did not correctly anticipate recurrent congestion or disruption and had a low preference for punctuality. Second, reasonably prudent individuals were characterized by a positive safety margin between zero and the threshold. These individuals made full use of the travel information provided and adapted their mobility behavior accordingly. Finally, excessive prudent individuals were characterized by a positive and large safety margin, which was higher than the threshold. These individuals had a large precautionary margin so much so that they tended to make less use of the travel information provided to change their mobility behavior. These results were in accordance with the H5 – *Commuters with a positive safety margin would use more travel information and, therefore, change their travel behavior.* To the best of our knowledge, these findings around the impact of travel information provision on commuter behavioral changes had never been documented in the literature.

Additionally, the study results stated that the role of travel information provision was quite limited. Indeed, while 73% of sample commuters declared using travel information sources (pre-trip or *en-route*) for their daily mobility within the research region, only 42% of them used it to adjust or modify their daily mobility behavior. On a global sample scale, it means that only 31% of the commuters are travel information behavioral change-sensitive. This modest share is all the more worrisome since, in France, most local public authorities are committed to promoting sustainable urban mobility by reducing the opportunity cost of information search on collective and shared transportation modes. Indeed, this opportunity cost is greater for public transportation, shared modes, and ecofriendly modes than for private cars. To achieve this goal, local public authorities can provide individuals with real-time and multimodal travel information for trips within urban areas. However, our findings highlight that travel information provision alone will not be enough to induce commuters' behavioral changes, *a fortiori*, in favor of more environment-friendly modes of transportation.

Future research would have to address the role of travel information provision on behavior changes in daily mobility in light of two events : the covid-19 pandemic, and the climate change issue. The Covid-19 pandemic has a global impact on travel behavior with successive lockdowns and the massive development of teleworking. In France, between the two first pandemic waves, the first studies show that public transport ridership has decreased by 28% in the Ile-de-France (Omnil, 2020).[21] In this context, the question arises of the relevant information to be provided to users in order to restore confidence in public transport (e.g., low or high period of occupancy rate, real time occupancy rate). Climate change issue will induce more and more adoption of low emission zones by local authority, and the the provision of travel information will become essential for users wishing to reach central business district.

[21] Source: `https://www.omnil.fr/IMG/pdf/resultats_mobilite_covid_sept-octobre_2020-internet.pdf`

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Acronyms

CITEPA	Technical Reference Center for Air Pollution and Climate Change
CU	Consumption unit
GHG	Greenhouse gases
ICT	Information and communications technology
INSEE	French national institute of statistics and economics studies
TAM	Transport de l'agglomeration de Montpellier

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