What is the role of active mobility habits in the relationship between self-determination and modal shift intentions? A mediation analysis

Hélène Bouscasse, Rim Rejeb, Helene Bouscasse, Aina Chalabaev, Sandrine Mathy, Rim Rejeb, Helene Bouscasse, Aina Chalabaev, Sandrine Mathy, Rim Rejeb, et al.

What is the role of active mobility habits in the relationship between self-determination and modal shift intentions? A mediation analysis

Rim Rejeb [*] [†] Hélène Bouscasse [‡] Aïna Chalabaev [§]
Sandrine Mathy [*]

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Abstract

There is little research on the role of motivations in predicting intentions to engage in pro-social or pro-environmental behaviours. In this article we rely on the Self-determination theory (SDT) to assess the relationship between individual motivations (autonomous and controlled) and intentions to modal shift. We additionally evaluate the mediating role of active mobility habits in this relationship. To do this we build and test theoretical models using structural equation modeling. The results show that if habits concerning the use of alternative modes to the car are not taken into account, the autonomous motivation has a significant impact on intention, but not controlled motivation. However, the introduction of habits in the model shows that they fully mediate the relationship between both motivations and intention. These results are useful for a better understanding of the psychological mechanisms of modal choice changes and the targeting of measures aimed at encouraging the use of active modes.

Keywords : self-determination theory, active mobility habit, intention, mediation
JEL calssification: D91, R49

[*] Grenoble Applied Economics Lab (GAEL), CNRS and Grenoble-Alpes University, Grenoble, France.
[†] rim.rejeb@yahoo.fr ; +33634431997; VEDECOM - mobiLAB, 23 bis All. des Marronniers, 78000 Versailles, France.
[‡] CESAER, Agrosup Dijon, INRAE, University Bourgogne Franche-Comte, Dijon, France.
[§] Laboratoire Sport en Environnement Social (SENS), Grenoble-Alpes University, Grenoble, France.

1 Introduction

Understanding the individual determinants underlying the adoption of less polluting and more active modes of transport is essential to design efficient individual behavioural change interventions improving air quality (Viana et al., 2020; Host et al., 2020; Johansson et al., 2017) and the population health (Flint and Cummins, 2016; Celis-Morales et al., 2017; Jaocob et al., 2019). Researchers actually underline the important role that the citizen plays as an active actor of change to achieve these objectives. This active individual involvement calls for motivations that could either be intrinsic or extrinsic (Thiermann and Sheate, 2020). Thus, the individual is no longer a passive receiver of public interventions but an active part and determinant of its success.

The study of individual engagement in pro-social or pro-environmental behaviour has long been done using theories that are based on the underlying assumption that individual decision is driven by norms and values (Steg and Nordlund, 2018). The most prominent example of such a theory is the Theory of Planned Behaviour (TPB) (Ajzen, 1991). It is based on the assumption that individuals make reasoned decisions and that behaviour is the result of the intention to engage in it. The stronger the intention, the more effort the person will put into the behaviour and the more likely he is willing to commit to implementing this behaviour (Steg and Norlund, 2012). In the TPB, the intention depends on three variables : the attitude towards the behaviour (positive or negative perception of the behaviour), the subjective norm (perceived social pressure) and the perceived behavioural control (ease or difficulty in performing the behaviour). The intentions implicitly indicate the level of motivation of the individual to engage in the behaviour, but the exact specification of these motivations are still lacking in the frame of the TPB.

Studies that have been interested in investigating the role of individual motivations more likely use the Self-Determination Theory (SDT) (Deci and Ryan, 1980; Deci et al., 1985). Despite its success in characterising the motivations behind the adoption of pro-environmental behaviour (Pelletier, 2002), we agree with Thiermann and Sheate (2020) on the fact that this theory "has not been on the radar of mainstream environmental psychologists" and even less environmental economists.

The SDT defines a continuum of motivations ranging from autonomous motivation (AM) to controlled motivation (CM). These motivations are related to fulfilling basic psychological needs (Vansteenkiste et al., 2020) to foster well-being and health. The adoption of a behaviour that is motivated through AM has meaning for the individual since it originates from internal factors of interest, enjoyment or satisfaction (eg. I take the bus because I enjoy watching the scenery). Whereas the adoption of a behaviour resulting from CM is not necessarily meaningful for the individual since it results from separate factors from the behaviour itself such as a sense of social pressure or feelings of guilt or shame. In this case, doing the behaviour would not be a source of satisfaction or pleasure for the individual.

In this article, we mobilise the SDT to study the relation between individual motivations (i.e. AM and CM) and intentions to modal shift to active mobility (public transport, bicycle and walking). The choice of an alternative mode to the car could be motivated by the well-being that the chosen mode generates. A person could choose to make her trip using public transport to enjoy the natural scenery or for the possibility that it offers for doing tasks (eg. reading, writing, sleeping) during the trip. Another person could choose walking or cycling for the health gains that they generate since they are valid means for practicing physical activity[1]. The literature about physical activity practice, and more generally psychological health studies, extensively implement SDT as a study framework for investigating motivations behind the adoption of healthier practices in everyday tasks (Niven and Markland, 2016; Hagger and Chatzisarantis, 2009; Moller et al., 2006). Considering transportation choice as a mean of practicing physical activity and trying to understand the motivations behind it further justifies our choice of the SDT as a theoretical study framework. Using this theory would bring a new perspective to the transportation study literature and further insights about the possible determinants of modal shifting and the influential levers for public interventions. Additionally, the present paper contributes in creating a bridge between transportation studies and health psychology studies.

Another factor of transport behaviour that is garnering interest in the literature is habits (Şimşekoğlu et al., 2015; Gardner, 2009): if the individual has strong intentions to choose an alternative mode to the car, habits that conflict with these intentions could prevent modal shift (Gardner, 2015). Based on the definition of habits as "behaviours that became automatic through repeated practice" (Radel et al., 2017), choosing everyday the mode of transport to go to work, to university or elsewhere is a repeated decision that could become a habit following an automatic decision process. Thus, if an individual has a habit of using the car automatically, deliberate consideration of different travel options may be limited (Eriksson et al., 2008). This would mean that using an alternative mode to the car is limited due to the pre-existing habit of using the car in addition to the lack of habitual use of public transport or bicycle, which we call active mobility habit. With the confirmed influence of habits on intentions, disrupting these habits would open a window through which it becomes possible to directly influence the intentions and motivating the individuals to consider other mobility options. Here comes the contribution of the present work which offers a better understanding of the intention-motivation relationship and the impact of active mobility habits on this relationship.

Despite the existence of a bundle of previous studies investigating the influence of habits on intentions (Verplanken and Whitmarsh, 2021; Gardner et al., 2020; Klöckner and Verplanken, 2018), we notice that less is known about the role of habits in the motivation-intention relationship, specifically in the case of studying mobility practices. This work is an attempt to fill this gap by not only assessing the motivation-intention relationship, but also testing the mediating role of active mobility habits in this relationship.

The results of structural equation models (SEM), ran on original data collected through a phone survey, show that AM (i.e. feeling of pleasure, belief in the usefulness and importance of modal shift) is positively correlated with higher active mobility habits and modal shift intentions. The effect of this type of motivation on intentions by considering habits is only indirect, confirming the strong influence of mobility habits on behaviour change. In contrast, CM (i.e. social pressure, fear of being criticized or judged) is negatively correlated with active mobility habits and does not significantly influence modal shift intentions.

The remaining of this article is organised as follows: section 2 presents the related literature. Section 3 displays the theoretical model and the tested hypotheses. Section 4 introduces the collected data and the methodology of analyses. Section 5 presents the results. Section 6 is a discussion with some conclusions.

2 Related literature

The SDT framework allows characterising the individual motivations considering the context and the environmental factors (Deci et al., 1985). Starting from the assumption that an individual is an active agent that has a goal-pursuit mindset (Ryan and Deci, 2000), he aims to engage in activities that allow full-filling mainly three innate psychological needs: 1) competence meaning that the person needs to believe in his skills and capability to succeed, 2) relatedness which concerns the need to feel connected to other people and have a sense of belonging and 3) autonomy which relates to the need to feel as the originator of the behaviour and having control over his personal actions. Meeting these needs is directly linked with better psychological health and overall well-being (Deci and Ryan, 2000).

In their description of motivations, Deci and Ryan (1980) use the SDT to describe the level of self-determination of the behaviour using an "autonomy-control continuum" of motivations (Thiermann and Sheate, 2020). Figure 1 illustrates this continuum according to which individuals whom motivation is more self-determined generally succeed in fulfilling the three previously mentioned needs. Thus the individual is responsible of his own actions, autonomous and feeling an alignment between his personal values and those resulting from the realisation of the action (De Groot and Steg, 2010; Hagger and Chatzisarantis, 2009). In the case of practicing physical activity through active mobility, an example of such motivation would be the feeling of pleasure when cycling or the believe of its positive consequences on one's health. On the contrary, when individuals' motivation is less self-determined, it is resulting from an external pressure that could be social or institutional. Thus, the individual feels controlled by these external forces which could take the form of feelings of guilt, shame or fear of disapproval (Thiermann and Sheate, 2020; Hagger and Chatzisarantis, 2009). For instance, if an individual works in an environment where his colleagues are usual cyclists who are always boasting about the benefits of this mode, coming everyday by car would make him feel a lack of belonging to this group and even ashamed of his mobility practices.

When the individual is neither controlled nor autonomously motivated, he is considered amotivated. Amotivation is defined as the absence of intention. Pelletier et al. (1999) explain this lack of motivation resulting in the fail to engage in pro-environmental behaviours by the individual's believes about the low capability of doing the behaviour or his believes about its low real impact on the environment (Deci and Ryan, 2000). In the case of using public transport, amotivation could be explained, for instance, by the unfamiliarity with the transport network or the pricing systems or ignorance of the positive impact of this behaviour on the environment and health. As for cycling, amotivation could be due to prior prejudices about the safety of this mode or excessive physical effort required to reach the destination.

Existing literature applying the SDT to study motivations confirm the positive relation between AM and intentions to engage in desirable behaviours (eg. recycling, physical activity, healthier diet) allowing for more extended commitment to the behaviour than the CM.

The study of De Groot and Steg (2010) demonstrates a significant relationship between individual motivations, specifically AM, and the intentions to engage in pro-environmental behaviour such as choosing an environmentally friendly car or making donations to an environmental organisation. A more recent study of Thiermann and Sheate (2020) also confirms the significant effect of AM on the probability to engage in a pro-environmental behaviour allowing for long-term positive social well-being. In the energy consumption field, Webb et al. (2013) used SEM with self-reported data on household energy-saving behaviours to find that AM directly predicts consumers' energy conservation intentions. However, CM do not seem to influence the intentions nor the behaviour. They actually identify AM as a better predictor of the studied behaviour than other more established determinants in the literature such as the past behaviour.

Motivations play also a significant role on the engagement in healthier practices. The meta-analysis of 36 health studies (mainly about physical activity) done by Hagger and Chatzisarantis (2009), through which they generated averaged correlation coefficients testing an integrated model joining the TPB and the SDT, demonstrated that AM predict intentions with a small but significant direct effect. This is an interesting result for us but motivations were measured as one latent construct confounding elements of both AM and CM. We feel that it would be better to distinguish the two motivations, AM from CM. This would give a more accurate view on the type of motivation that influences the studied relations.

It is clear that motivations are a significant determinant of human behaviour, in particularly, AM. In this regard, Moller et al. (2006) state that AM and choice, as opposed to CM and choice, "are positively associated with maintained behaviour change, effective performance, and psychological well-being".

Despite the identified significant effect of motivations on intentions, and considering that transportation practices have both environmental and health consequences, the existing transportation studies rarely consider SDT as a study framework. To the best of our knowledge, we at most find one study by Niven and Markland (2016) about walking behaviour but considering it only as a mean to engage in physical activity through different walking purposes among which is transportation. It is actually the purpose of the present work to contribute to this small literature trying to better understand the motivating process underpinning the individual intentions to modal shift. However, since our aim is to explain intentions, we only consider individuals that have a minimum of motivation. Thus, amotivated individuals were discarded using filters in our survey.

Using a health psychological theory such as the SDT in transportation studies to understand modal choice brings a new perspective to this discipline. We actually believe that understanding and modifying mobility choices has a multidimensional aspect influencing individual health and the environment. Thus, scientists from concerned fields (eg. transportation, urban planning, health and environment sciences) should work together and use their respective scientific approaches as complementary to have a better understanding of ways to efficiently influence mobility choices.

Despite their interesting results, such collaborations are emerging but remain scarce. For instance, a recent study of Koszowski et al. (2019) brought together insights from transport planning, urban planning and public health proposing policy measures supporting active mobility. Their review demonstrated the existence of common objectives between disciplines and sectors interested in active mobility. The review of Sallis et al. (2004) also encouraged collaborations between researchers identifying possible bridges to create between transportation (urban design and transport) and health (physical activity) studies. This type of collaborations allows formulating consistent recommendations for public authorities to implement their interventions' design. The present work is an additional contribution to these interdisciplinary transportation studies.

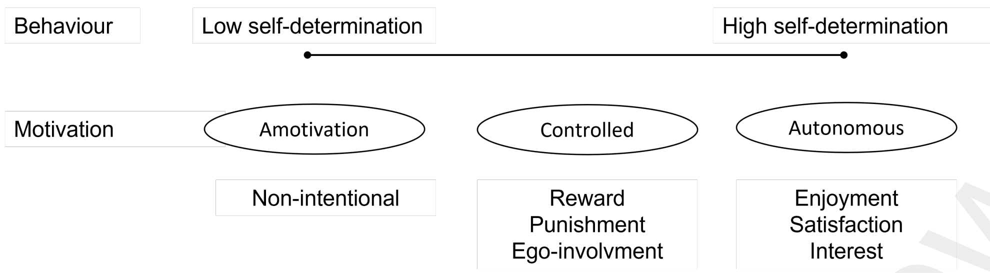


Figure 1: The self-determination continuum

3 Theoretical model and hypotheses

Based on the idea that a behaviour is the result of a pre-identified intention, we focus here on explaining the individual intentions to modal shift from the car to active modes. We build a theoretical model, presented in figure 2, to test the relationships between AM, CM and active mobility habits in predicting the intentions of choosing alternatives to the private car. We make assumptions on the way socio-demographic variables (age, gender, income, level of mobility[2], zone of residence and number of owned vehicles) influence the three latent variables.

We suppose that motivations are the main predictor of intentions and do not initially consider habits in the study of this relationship. For both motivations, AM and CM, we expect a positive relation with more motivated individuals having higher intentions to use alternative modes (H1 and H2). These assumptions are grounded on the previously presented literature in which motivations, especially AM, were positively related to intentions to engage in pro-environmental behaviours and physical activity (eg. Webb et al., 2013; Hagger and Chatzisarantis, 2009).

Aware that yesterday's habits may prevent change in tomorrow's transportation behaviour (Klöckner and Verplanken, 2018), we extend the first model of the motivation-intention relationship by introducing habits. Traditionally, the studies of the determinants of modal shifting introduce habits as the past choice or automatic choice of the car (eg. Gardner et al., 2020, Ramos et al., 2020). In the present model, we instead introduce the mobility habits as a measure of the automaticity of choosing active mobility. Thus, we expect a positive relation between active mobility habits and intentions to modal shift. We actually consider that the fail to change mobility practices is partly due to a lack of practice of the active modes resulting in less knowledge about the available options other than the private car. This makes it more costly for the individual to start practicing it and creating active mobility habits.

Introducing this variable in the motivation-intention relationship would allow us to better understand the interactions between these variables and build the motivational process behind modal shifting. We expect active mobility habits to be a mediator between both motivations and intentions (see $H1'$ and $H2'$). This means that being more self-determinedly motivated could not only have a direct effect on intentions to modal shift but also help to build active mobility habits which in turn generates an indirect effect through active mobility habits of motivations on intentions.

Previous studies interested in assessing the motivation-intention relationship have generally introduced past behaviour or habits as a direct determinant of intentions or as a moderator influencing other determinants of intentions (Hagger and Chatzisarantis, 2009; Webb et al., 2013). Less is known about the possible effect of active mobility habits on intentions if considered as a mediator of a previously identified relation (i.e here, the motivation-intention relationship).

Regarding the socio-demographic variables, we expect that they influence all the latent constructs including the dependent variable of intentions. We expect younger individuals to have higher intentions to modal shift. In the literature, the age effect depends on the specific type of active mode: on the one hand, younger individuals cycle more (Muñoz et al., 2016) and on the other hand, older individuals use public transport more (Ton et al., 2019). In terms of gender, we do not think that we would find a significant difference between male and female to modal shift. Indeed, the literature does not reach a consensus in this regard (De Witte et al., 2013; Best and Lanzendorf, 2005). For the income effect, we expect that a higher income would influence negatively the intentions to modal shift. Previous studies assessing the income effect on modal choice have identified a significant relation. For example, car owners tend to be higher income populations showing a positive relationship between income and private car use (Tao et al., 2019; De Witte et al., 2013). Besides, the level of mobility which reflects the frequency of trips done in a day related to the occupation is expected to influence negatively the intentions to modal shift. We think that individuals who are more mobile would opt to using the fastest mode of transport which is generally considered to be the car. Referring to the literature, usual car users struggle to consider other options due to generalised misconceptions (Ramos et al., 2020) about the alternatives such as the perceived lack of control for public transport or lack of safety when using the bicycle. The zone of residence is also expected to influence our model. We expect that people who live in urban areas with well-developed transportation network and cycling paths are more likely to have higher intentions to modal shift. Indeed, the review done by De Witte et al. (2013) about the determinants of mobility confirms this idea. Lastly, we believe that having a private vehicle in the household would encourage the individuals to keep using the car instead of changing their practices (De Witte et al., 2013), especially if they have multiple cars.

The hypotheses testing the relation between autonomous motivation, controlled motivation, active mobility habits and intentions are as follows

H1: More autonomously motivated individuals have higher intentions to modal shift

$H1'$: ... and having the habits of using active modes is a mediator of this relation

H2: More controlled individuals have higher intentions to modal shift

$H2'$: ... and having the habits of using active modes is a mediator of this relation

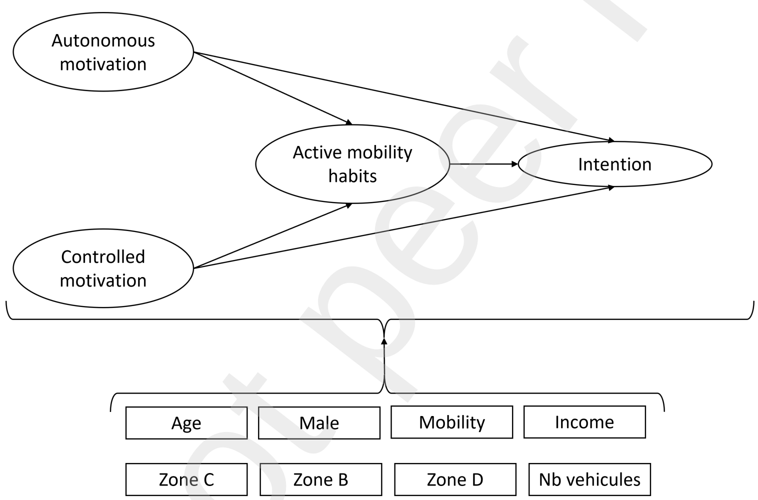


Figure 2: The theoretical model

4 Data and methods

4.1 Participants and procedure

We use original data collected through a phone survey conducted between April and May 2019 within the QAMECS-SHS project[3]. Table 1 presents a summary of the descriptive statistics of some socio-demographic variables. We have a sub-sample of 1,033 participants[4] living in Grenoble Metropolitan Area among which 49% are male with 50 years old mean age and around € 2900 mean income. A majority of 65% of the sample are mobile individuals making a high number of trips per day. Besides, most of our sample is composed of individuals living in or close to the city, so in zones that are generally well-connected in terms of transportation services and infrastructure (public transport, cycling paths, etc.): 34% live in the city of Grenoble (Zone A), 37% in the adjacent areas called the "Urban heart" (Zone B), 10% live in peri-urban and rural territories (Zone C) and the remaining 19% are residents of Grenoble's neighbouring inter-municipalities (Zone D, Grésivaudan and Voironnais).

Table 1: Summary of the socio-demographic variables

Variable	Label	Code	Proportion (%)
Male	Gender	=1 if male =0 if female	48.79
Mobility	Level of mobility	=1 if mobile = 0 if less mobile	65.34
ZoneA	Resident of zone A (reference zone)	=1 if resident of zone A (Grenoble city) = 0 if not	33.88
ZoneB	Resident of zone B	=1 if resident of zone B ("Urban heart" of the metropolis) = 0 if not	36.69
ZoneC	Resident of zone C	=1 if resident of zone C (Peri-urban and rural territories) = 0 if not	10.36
ZoneD	Resident of zone D	=1 if resident of zone D (Grésivaudan or Voironnais) = 0 if not	19.07
			Mean (SD)
Age	Age in number of years	Continuous variable	50.10 (18.49)
Income	level of income in €	Continuous variable	2940.12 (1577.05)
Nb vehicles	Number of vehicle per household	Continuous variable	1.41 (1.03)

4.2 Measures

Based on the literature, we introduced in the survey the items measuring our variables of interest. Then, we made a series of Exploratory factor analyses (EFA) and Confirmatory factor analyses (CFA), explained in more detail in the next section, to test the robustness of the latent constructs and to build reliable models. A summary of the used items is presented in table 2 with some descriptive statistics related to the participants' answers.

Intentions We measure the intentions to modal shift by determining the stage-of-change (Biehl et al., 2018) at which the participant is. To do this, we ask the participant to declare on a 5-points scale whether they 1.do not intend to begin using active modes, 2. are thinking about it, 3. have serious intentions to start using alternatives, 4. already use them at least three times a week or 5. already use them every day.

Behavioural automaticity (active mobility habits) Habits could be measured using either frequency measures or automaticty measures. In our case, we choose to use the latter. According to Gardner et al. (2012) and Gardner (2012), measuring habits with automaticity measures is more reliable than just counting frequencies. However, previous studies assessing the relation between our variables of interest measure the past behaviour relying on frequencies (Webb et al., 2013; Hagger and Chatzisarantis, 2009). Thus, testing these relations with automaticity as the measure of habits is another contribution of this work. We implement the Self-Report Behavioural Automaticity Index (SRBAI, Gardner et al., 2012) to measure automaticity of choosing active modes as alternatives to the private car. The measure of active mobility habit is composed of four items with 5-points Likert scales ranging from 1 for "strongly disagree" to 5 for "strongly agree".

Motivations (AM and CM) We measure the individual motivations as two separate latent constructs, distinguishing AM from CM, following the work of Brunet et al. (2015). AM is composed of five items asking the participants to declare the degree to which their motivations to use alternatives to the car are the result of personal interest, satisfaction and enjoyment (eg. If you intend to use an alternative transportation mode to the car on the majority of your trips, it's mainly because you like it, Q9 in table 2). This is done using 5-points Likert scales ranging from 1 for "strongly disagree" to 5 for "strongly agree". Regarding CM, it is composed of four items asking the participants about the degree to which their motivations to use alternatives to the car are the result of external punishment or reward (eg. If you intend to use an alternative transportation mode to the car on the majority of your trips, it's mainly because people around you criticise you if you do not use an alternative mode, Q13 in table 2). This is also done using 5-points Likert scales ranging from 1 for "strongly disagree" to 5 for "strongly agree".

Table 2: List of items measuring the latent constructs of the model

Latent construct	Adapted from	Item		Scale	Mean (SD)
Intention	Biehl et al. (2018) and Godin (2013)	Q1	Do you use an alternative mode of transportation to the private car for at least 3 trips per week (including weekends)?	1.No, I don't intend to begin, 2.No, I'm thinking about it, 3.No, I seriously intend to start, 4.Yes, at least 3 times a week, 5.Yes, every day or almost every day	4.7 (0.75)
Active mobility habits	Gardner et al. (2012)		Deciding to use an alternative mode of transportation to the car is something :	1=Strongly Disagree to 5=Strongly Agree	
		Q2	That you do automatically		3.58 (1.42)
		Q3	That you do without thinking about it		3.52 (1.44)
		Q4	That you do without having to consciously remember		3.55 (1.42)
		Q5	That you start doing before you realize it		3.15 (1.45)
Autonomous motivation (AM)	Brunet et al. (2015)		If you intend to use an alternative mode of transportation to the car on the majority of your trips, it's mainly because	1=Strongly Disagree to 5=Strongly Agree	
		Q6	... you believe it's important		3.82 (1.31)
		Q7	...for the pleasure of using an alternative mode of transportation (e.g., walking, cycling)		3.27 (1.40)
		Q8	... it gives you a plus		3.42 (1.38)
		Q9	... you like it		3.36 (1.36)
		Q10	... for your health		3.51 (1.36)
Controlled motivation (CM)	Brunet et al. (2015)	Q11	... people around you are pushing you to do it	1=Strongly Disagree to 5=Strongly Agree	1.76 (1.12)
		Q12	... you would feel ashamed not to do it		2.05 (1.25)
		Q13	... people around you criticise you if you do not use an alternative mode		1.48 (0.94)
		Q14	... you would feel guilty about not using an alternative mode of transportation		2.25 (1.34)

4.3 Data analyses

When studying relationships between latent variables that are measured with observed items, the most appropriate and widely used method is Structural equation Modeling (SEM). The objective of a SEM is to test hypotheses of relationships between several variables of a theoretical model.
To guarantee a well-established and reliable model, we assess the internal consistency of the scales using EFA and CFA, then test the relations between the latent constructs using SEM.

Exploratory factor analyses (EFA) Carrying out an EFA allows us to validate scales of items in a questionnaire and derive a construct (e.g. active mobility habits) for a group of items (e.g. Q2 to Q5). This statistical technique is done following a number of steps (Samuels, 2017) that we describe in more details in appendix 6.

We start by doing a series of tests verifying the adequacy of doing an EFA on our data (Kaiser-Meyer-Olkin measure of sampling adequacy test, Bartlett's test of sphericity, etc.). The items that we focus on are the questions Q2 to Q14 (see table 2).

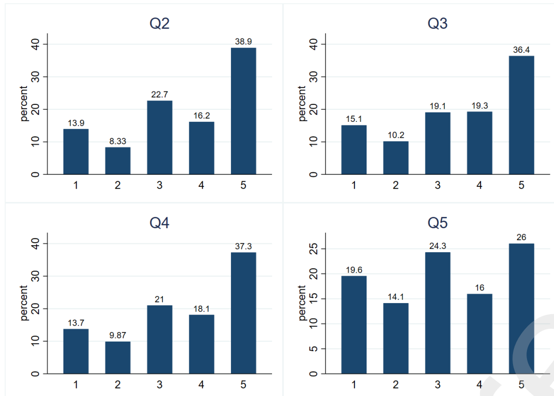
The EFA allowed us to identify 3 latent constructs with a good level of internal consistency (referring to their Cronbach's alpha coefficients): active mobility habits, AM and CM.

Confirmatory factor analyses (CFA) After the EFA, we move to confirmatory factor analyses (also known as measurement model in SEM). CFA is used to confirm the existence of relations between the constructs and the items that measure them. The relations are usually supported by a theoretical model and this statistical technique intervenes, as its name suggests, to confirm empirically the supposed correlations presented in the theoretical model.

CFA relies on several statistical tests to determine the adequacy of model fit to the data. The model estimated is assessed using model fit indices such as the chi-square test, the Root Mean Square Error of Approximation (RMSEA), the Comparative Fit Index (CFI) and the Tucker–Lewis index (TLI), etc. If the model is found to be well-adjusted to the data, we can move to structural equation modeling.

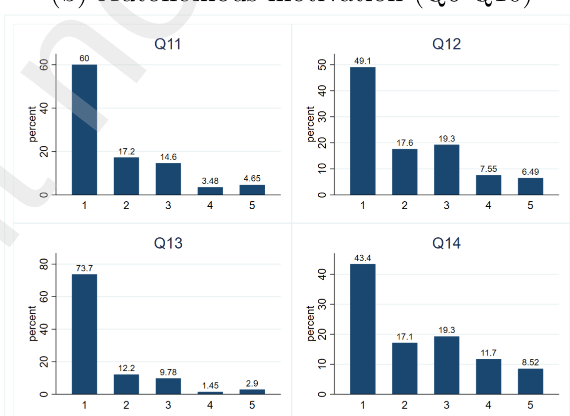
When estimating the model it is important to choose the appropriate estimation method to the type of data. In general, CFA is done using the Maximum Likelihood (ML) estimation method. However, using this method is suitable only when the data is continuous and normally distributed. Since our questions are 5-points Likert scales, the data that we are analysing is ordinal and does not follow a normal distribution[5]. Figure 3 presents the distribution of the answers to the used items. Thus, using ML is not suitable (Rhemtulla et al., 2012; Bouscasse et al., 2018). Instead, we choose the diagonally Weighted Least

Squares method with a Mean and Variance correction (WLSMV) which was demonstrated to perform better with ordinal data (Li, 2014).



(a) Active mobility habits (Q2-Q5)

(b) Autonomous motivation (Q6-Q10)



(c) Controlled motivation (Q11-Q14)

Figure 3: Distribution of the answers to the items Q2 to Q14

Mediation analyses with structural equation modeling Mediation analyses consists of supposing that there is a variable, called a mediator, that explains the relationship between two other variables. This kind of method helps to understand a decision process and visualise the contribution of each one of its elements. In the present study, we build a model to test the mediating role of active mobility habits in the motivations-intention relationship. We control for the effects of the socio-demographic variables.

The mediation analysis is done following three main steps described by Baron and Kenny (1986). These steps consist in building three sub-models for each studied mediation relation. First, a model involving only the independent (i.e AM and CM) and the dependent variable (i.e Intentions) is estimated. If this relation is significant, a second regression is done to verify the significance of the relation between the independent variables (AM and CM) and the mediator (active mobility habits). A final regression is done combining the mediator, the independent and the dependent variables. For many years, these steps were performed using multiple regression analyses. But it has been shown that this method is not very appropriate when making mediation analyses because it presumes the directions of the causal relationships. Instead, SEM was demonstrated to be more appropriate for mediation analyses. According to Gunzler et al. (2013), the advantages of using SEM are mainly related to the ease of interpretation and estimation in testing mediation hypotheses which justifies our choice of this method to carry out our analyses.

When doing mediation analyses, it is important to start by verifying the significance of the direct effect of the independent variable on the dependent variable. If it is significant, we add the mediator to the model. The direct effect is then expected to be reduced since some of the effect is now explained by the mediator. If the direct effect is reduced but stays significant, the mediation effect is called "partial mediation". But if the direct effect is reduced and becomes non-significant, then the mediation is called "complete mediation" or "full mediation" (Awang, 2012). We test the significance of the indirect effects using Sobel test (or Delta method) (Sobel, 1982).

5 Results

We build SEM testing the mediation effect of active mobility habits in the motivation-intention relationship, aiming to better understand the defining determinants of modal shift intentions. SEM is a combination of CFA and regression models used to understand the paths between the latent constructs. The following section is a presentation of the results of the analyses that we carried to build and test our model helping us respond to our research question. We start by presenting the EFA and the CFA (measurement model) results. Then, the results of the mediation analyses.

5.1 Exploratory factor analyses (EFA)

Following the steps detailed in appendix 6, we performed an EFA of the items Q2 to Q14. As previously mentioned, we identified three factors presenting good levels of internal consistency based on their Cronbach's alpha coefficients ($\alpha > 0.6$). Table 3 presents a summary of the results of the EFA which allowed to identify three factors without dropping any of the included items. The first factor ($\alpha = 0.88$) refers to active mobility habits and is composed of items Q2 to Q5 with factors loading ranging from 0.78 to 0.87. The second factor ($\alpha = 0.78$) refers to SDM including the items Q6 to Q10 with factors loading ranging from 0.64 to 0.73. The final factor ($\alpha = 0.68$) refers to NSDM and is composed of items Q11 to Q14. The factors loading of these items range from 0.66 to 0.75.

Table 3: Results of the exploratory factor analyses of the items Q2 to Q14

	Questions	**Factor Loading**	α
Factor 1 : Active mobility habits	Q2. That you do without having to consciously remember	0.87	*0.88*
	Q3. That you do without thinking about it	0.86	
	Q4. That you do automatically	0.85	
	Q5. That you start doing before you realize it	0.78	
Factor 2 : Autonomous motivation	Q6. ... you like it	0.73	*0.78*
	Q7. ...for the pleasure of using an alternative mode of transportation	0.72	
	Q8. ... for your health	0.71	
	Q9. ... you believe it's important	0.64	
	Q10. ... it gives you a plus	0.64	
Factor 3 : Controlled motivation	Q11. ... you would feel ashamed not to do it	0.75	*0.68*
	Q12. ... people around you are pushing you to do it	0.74	
	Q13. ... you would feel guilty about not using an alternative mode of transportation	0.71	
	Q14. ... people around you criticize you if you don't use an alternative mode	0.66	

Notes:
All chosen factor loadings are above 0.4
α: Cronbach's alpha coefficient

5.2 Confirmatory factor analyses (CFA)

Using the three latent constructs identified through the EFA, we carry out the factor analyses by doing a CFA. The used estimation method is WLSMV since we are manipulating ordinal data. The model tested is presented in figure 4.

To empirically judge the quality of a model using CFA, we check its fit indices. In our case, we have a chi-square test $\chi^2(62)=$ 449.470 with p-value < 0.05. If p-value is greater than 0.05, this indicates that there is little difference between the expected and the observed covariance matrices. A more informative index is the Root Mean Square Error of Approximation (RMSEA) which is here equal to 0.078. This suggests having an acceptable fit of the data to the model since we have a value between 0.05 and 0.08 (Hu and Bentler, 1999; Kaplan, 2008). The values of the comparative fit index (CFI) and the Tucker–Lewis index (TLI), 0.972 and 0.965 respectively, are above the recommended threshold of 0.95 which also means that our model fits well our data. The model presented here supposes correlations only between the latent variables. Correlations between the residuals of the items could also exist by verifying the modification indices[6] which could further improve our model fit.

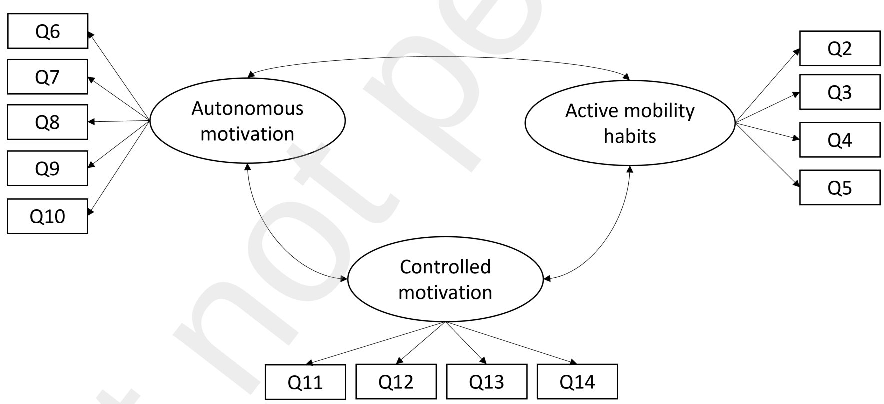


Figure 4: Model tested through confirmatory factor analyses

5.3 Mediation analyses using SEM

We conduct the mediation analyses following the steps of Baron and Kenny (1986) by creating sub-models that are summarised in table 4. Model M1a tests the direct effect of both motivations on intentions. Model M1b tests the indirect effect of AM on intentions through active mobility habits. Model M1c tests the indirect effect of CM on intentions through active mobility habits. Besides, M1d tests the indirect effect of AM and CM on intentions through active mobility habits. The results of the estimations of these models are presented in table 5.

Table 4: Summary of the estimated models

Hypothesis	**Tested effect**	**Models**
H1: More autonomously motivated individuals have higher intentions to modal shift	Direct	M1a
H1': ... and having the habits of using alternative modes is a mediator of this relation	Indirect	M1b & M1d
H2: More controlled individuals have higher intentions to modal shift	Direct	M1a
H2': ... and having the habits of using alternative modes is a mediator of this relation	Indirect	M1c & M1d

The first simple regression, M1a in figure 5, assessing the direct effect of the two types of motivations demonstrates a significant effect of AM (0.118, p-value= 0.047) but not of CM (-0.055, p-value=0.359) on the intentions to modal shift.

Introducing the active mobility habits as a possible mediator, model M1b in figure 6, the results show a very significant indirect effect ($0.187 = 0.591 \times 0.315$, p-value=0.000) of AM on intentions going through the habits. However, the direct effect of CM on intentions becomes non significant (-0.088, p-value=0.225). This means that we are in the case of a full mediation effect.

Regarding AM, since we have a non significant direct effect of this type of motivation on intentions, it is not possible to carry on the mediation analysis evaluating the indirect effect of AM through active mobility habits. Thus, we discard the model M1c and we do not present its results in table 5.

We complement the model M1b by introducing the CM to take into account the correlation that may exist between the two types of motivation in determining the intentions (see model M1d presented in figure 7). We notice that the direct effects of both motivations on intentions remain non significant. However, these motivations influence significantly the active mobility habits. The AM are actually positively associated to stronger active mobility habits (0.648, p-value=0.000) contrary to CM which are negatively associated to these habits (-0.148, p-value=0.000).

This results in significant indirect effects of motivations on intentions through habits as the mediator. The indirect effect of AM on intentions is positive ($0.203 = 0.648 \times 0.313, p-value = 0.000$). Whereas CM has a negative indirect effect on intentions ($-0.046 = -0.148 \times$

$0.313, p - value = 0.003$). Having significant indirect effects and non significant direct effects means that active mobility habits fully mediate the relation between motivations and intentions (see table 6).

Looking to the effects of the socio-demographic variables on each latent construct in the most exhaustive model (model M1d), we find that age influences significantly uniquely the intentions to modal shift: older participants are less likely to have higher intentions to modal shift (-1.099, p-value<0.1). This result contradicts the ones presented in the meta-analysis of Aldred et al. (2017) who found that older individuals have lower preferences for the private vehicle, so relying more on active mobility. The refrain of our older participants from having intentions to modal shift could be related not only to latent factors influencing the level of these intentions but also to health and urban design factors, as mentioned in the study of Klicnik and Dogra (2019).

Furthermore, our results show that the zone of residence influences all the constructs but in different ways. Considering zone A (Grenoble city) as the reference zone, being a resident of a non-central zone is negatively associated with AM (zone B: -0.049, zone C:-0.119, zone D:-0.103) and active mobility habits (zone B: -0.039, zone C:-0.094, zone D:-0.081). For both constructs, we notice a sort of a gradient: Negative coefficients are higher for zone C compared to zone B. This gradient is inverted when reaching zone D. An explanation may be that residents of zone D make less frequent trips to Grenoble city so they are less sensitive to the distance influencing their AM and active mobility habits. For the two other zones (B and C), the negative effect may be larger because in these zones the transportation network is less developed compared to zone A. Thus, usually using alternatives to the car and being individually motivated to do so is less likely. In contrast, we find that living further away from zone A is positively related to higher CM. This is true especially for residents of zone D (0.087, p-value<0.05). Residents of zones closer to zone A do not feel the social pressure and shame of not using alternatives to the car, whereas residents of zone D could be motivated to modal shift through this type of motivation. The estimation results also demonstrate that being a resident of further zones away from Grenoble city is negatively associated with intentions to modal shift. This effect is the strongest when comparing zones B to A and decreases as one moves away from zone A. This could also be related to the quality of the transportation network in the zones. Since the network in zone C is less developed, people usually consider less the alternatives to the car in their modal choice. Thus, intentions and zones away from the city center are negatively associated.

Car ownership is negatively associated with AM (-0.092, p-value<0.01) and active mobility habits (-0.073, p-value<0.01). This result emphasizes the idea that having a car in the household is a barrier to considering alternatives to the car (Tao et al., 2019).

Lastly, the gender, the individual's level of mobility and his income level do not influence significantly any of the studied latent constructs.

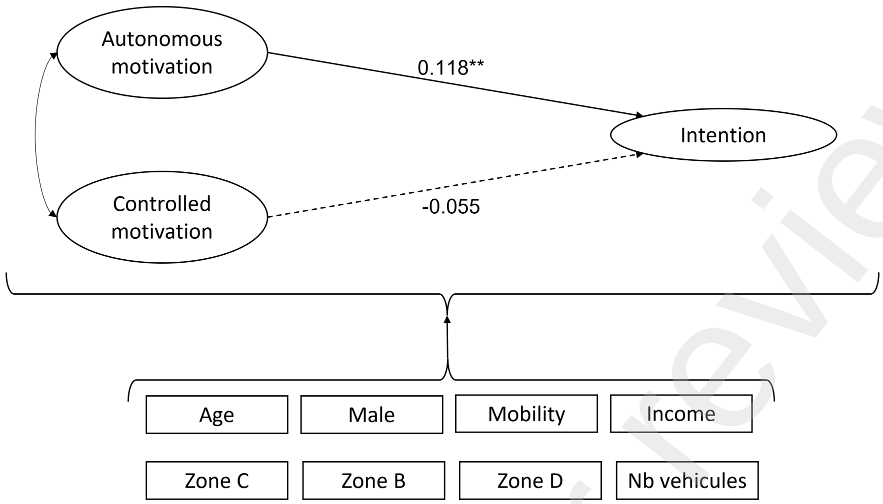


Figure 5: Standardised regression weights of model M1a

$^{**}p < 0.05$; $^{***}p < 0.01$
RMSEA = 0.037

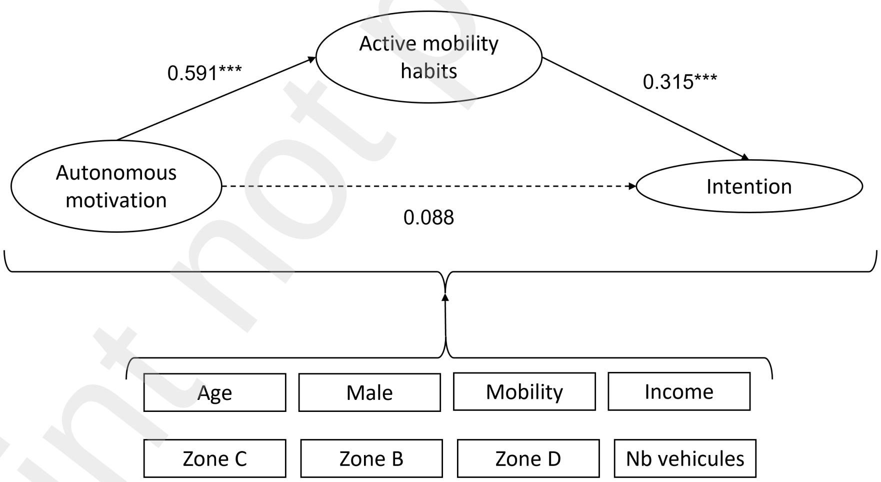


Figure 6: Standardised regression weights of model M1b

$^{**}p < 0.05$; $^{***}p < 0.01$
RMSEA = 0.033

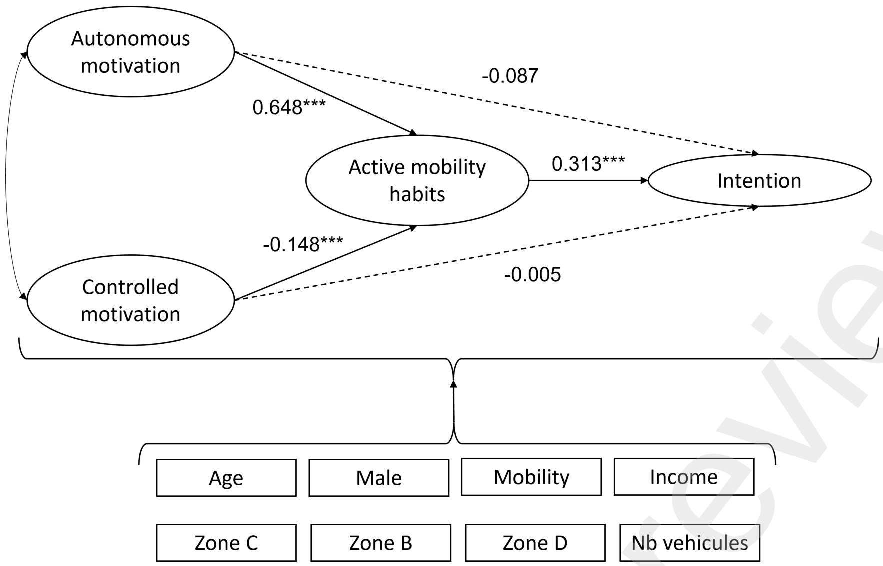


Figure 7: Standardised regression weights of model M1d

$^{**}p < 0.05$; $^{***}p < 0.01$
RMSEA $= 0.045$

Table 5: Estimation results

Dependent variable	Explanatory variable	M1a	M1b	M1d
AM	Male	-0.070	-0.070 (0.046)**	-0.036 (0.033)
	Age	0.924 (0.008)***	0.934 (0.007)***	0.228 (0.005)
	Age^2	-0.822 (0,000)***	-0.833 (0.000)***	-0.206 (0.000)
	Income	0.065 (0.000)*	0.066 (0.000)*	0.019 (0.000)
	Mobility	0.047 (0.073)	0.045 (0.065)	0.033 (0.048)
	ZoneB	-0.030 (0.063)	-0.029 (0.056)	-0.049 (0.041)*
	ZoneC	-0.059 (0.063)	-0.066 (0.081)*	-0.119 (0.061)***
	ZoneD	-0.083 (0.092)**	-0.088 (0.070)**	-0.103 (0.049)***
	Nb vehicles	-0.076 (0.027)**	-0.078 (0.024)**	-0.092 (0.016)***
CM	Male	-0.007		-0.015 (0.038)
	Age	-0.537 (0.007)**		-0.412 (0.006)*
	Age^2	0.492 (0.000)**		0.381 (0.000)*
	Income	-0.004 (0.000)		0.001 (0.000)
	Mobility	0.018 (0.060)		0.023 (0.054)
	ZoneB	0.066 (0.051)		0.065 (0.046)
	ZoneC	0.028 (0.081)		0.033 (0.073)
	ZoneD	0.089 (0.063)**		0.087 (0.058)**
	Nb vehicles	-0.077 (0.022)*		-0.071 (0.021)*
Active mobility habit	AM		0.591 (0.045)***	0.648 (0.045)***
	CM			-0.148 (0.059)***
	Male		0.012 (0.054)	-0.028 (0.033)
	Age		-0.555 (0.009)***	0.180 (0.005)
	Age^2		0.487 (0.000)***	-0.162 (0.000)
	Income		-0.037 (0.000)	0.015 (0.000)
	Mobility		0.009 (0.062)	0.026 (0.048)
	ZoneB		-0.073 (0.062)**	-0.039 (0.041)*
	ZoneC		-0.167 (0.104)***	-0.094 (0.061)***
	ZoneD		-0.117 (0.084)***	-0.081 (0.049)***
	Nb vehicles		-0.081 (0.031)**	-0.073 (0.016)***
Intention	AM	0.118 (0.085)**	-0.088 (0.117)	-0.087 (0.122)
	CM	-0.055 (0.109)		-0.005 (0.111)
	Active mobility habit		0.315 (0.077)***	0.313 (0.079)***
	Male	-0.052 (0.097)	-0.057 (0.097)	-0.048 (0.096)
	Age	-1.134 (0.018)***	-0.912 (0.018)***	-1.099 (0.017)***
	Age^2	1.148 (0.000)***	0.953 (0.000)***	1.119 (0.000)***
	Income	-0.054 (0.000)	-0.041 (0.000)	-0.053 (0.000)
	Mobility	0.098 (0.128)	0.095 (0.130)	0.091 (0.128)
	ZoneB	-0.186 (0.130)***	-0.167 (0.128)***	-0.172 (0.128)***
	ZoneC	-0.171 (0.171)***	-0.121 (0.176)**	-0.135 (0.174)***
	ZoneD	-0.115 (0.150)**	-0.084 (0.149)	-0.087 (0.149)
	Nb vehicles	-0.071 (0.058)	-0.042 (0.057)	-0.046 (0.057)
Covariances	AM $\sim\sim$CM	0.459 (0.026)***		0.429 (0.026)***
	Q6 $\sim\sim$Q10	-0.321 (0.081)		-1.219 (0.115)*
	Q5 $\sim\sim$Q9	0.427 (0.037)***		0.450 (0.040)***
	Q8 $\sim\sim$Q12	0.357 (0.022)***	0.244 (0.025)***	0.300 (0.023)***
	Q7 $\sim\sim$Q13		0.190 (0.025)***	
Goodness Of Fit	RMSEA	0.037	0.033	0.045
	TLI	0.987	0.996	0.986
	CFI	0.974	0.991	0.974

Notes:
AM = autonomous motivation, CM = controlled motivation
$^*p < 0.1$;$^{**}p < 0.05$; $^{***}p < 0.01$
Standard error between parentheses

Table 6: Summary of the mediation results (M1d)

Hypotheses	Estimate (Standardised)	p-value	Results on hypotheses	Results on mediation
AM has a significant effect on active mobility habit	0.648	0.000	Supported	
CM has a significant effect on active mobility habit	-0.148	0.000	Supported	
active mobility habit has a significant effect on intention	0.313	0.000	Supported	Full mediation
AM has a significant effect on intention	-0.087	0.288	Rejected	
CM has a significant effect on intention	-0.005	0.924	Rejected	

6 Discussion and conclusion

In this article, we assess the motivation-intention relationship assuming that intentions to modal shift are the result of AM and CM. We also investigate the role of active mobility habits in this relationship as a possible mediator. To this end, we run SEM including these latent constructs and controlling for the effect of socio-demographic determinants.

Our results are consistent with the findings of previous studies. We find, without considering habits, significant but small direct effect of motivations on intentions. This is similar to the result presented by Hagger and Chatzisarantis (2009). Additionally, the distinction between the two constructs AM and CM confirms that this effect on intentions comes mainly from AM. This is similar to the findings of Webb et al. (2013) who identified a significant direct effect of AM on intentions and behaviour to save energy but CM did not predict the intentions nor the behaviour.

The identified direct effect becomes non significant when including active mobility habits as a mediator of the motivation-intention relationship. Thus, active mobility habits overpower the direct effect of AM on intentions. This confirms the high association between habits and intentions, especially when they are going in the same direction as mentioned by Gardner et al. (2020).

However, both types of motivations seem to be powerful predictors of mobility habits but with different signs. CM is negatively associated with active mobility habits meaning that being socially pressured to adopt alternative modes to the car reduces the habits of using active modes. Whereas, AM is positively associated with active mobility habits meaning that those who personally enjoy using active modes are more likely to develop a habit for that modal choice. These results also go along previous findings, specifically in the literature on physical activity practice (Vasconcellos et al., 2020). Individuals are actually more likely to regularly engage in physical activity if they are more autonomously motivated than those externally motivated (Gardner and Lally, 2013).

In light of these results, public recommendations could be provided. First, public authorities need to increase people's AM to use active modes. This could be done through measures allowing for individuals to feel more in control of their own decisions and better perceive the utility of changing their mobility practices. Such measures could take the form of public informative campaigns about the positive consequences of modal shifting on improving the environment or reducing health risks. Bouscasse et al. (2022) study this and show that providing information about reduced risk of developing cardiovascular disease thanks to modal shifting increases the probability of people choosing active modes. Another example of a public measure that stems from our work is the improvement of cycling infrastructure. Safer cycle paths would change perceptions about the lack of safety of cycling and make cycling more enjoyable.

Second, the results about CM and its negative effects on active mobility habits and intentions suggest that interventions based on guilt or shame should be avoided. For example, using messages communicating the negative consequences of using the private car would actually be counterproductive resulting in less modal shifting. We recommend rather focusing on communicating positive messages about the benefits of modal shifting.

Third, these results indicate to public authorities the importance of considering habits in the design of behaviour change interventions. The strong effect identified for habits suggests the need to find ways to disrupt undesirable habits. In parallel, there is a need to promote the construction of habits of the desired behaviour (here, active mobility). This could take different forms such as giving free test days of the city bicycle or the public transport network or help usual car users discover electric bicycles as an active alternative to commute that is relatively fast and not excessively physically tiring on long distances.

The present work has provided more clarity on how desirable habits are influenced by motivations: There is a strong link between habits and the individual's internal beliefs and attitudes rather than the external pressures (social or institutional) that the individual may endure from his environment.

Some limitations with the present work should be mentioned as well as some possible future avenues of research. First, our results highly depend on the way we measured our latent variables. Even though we based our choice of measures on the literature and tested their robustness, using other scales could give different results than the ones found here. Second, we made a distinction between two types of motivations with the AM having more significant effects. Our results do not show a significant effect of CM on intentions. The CM may be linked to the pressure that family, friends or professional environment may exert. However, the entourage may also be linked with AM having a positive effect on intentions to modal shift. If an individual has a friend that uses the public transport instead of the car to commute, this person may choose the public transport not necessarily because of the pressure felt from this friend but because he enjoys the ride with them. Lambotte et al. (2022) actually show that the professional network has a significant impact on the choice of active modes. It would therefore be useful to conduct further research on the role of the entourage and the motivations in the choice of alternative modes of transport to the car.

Third, our work was an attempt to implement the SDT in the study of mobility behaviour, when it is usually used in physical activity and health studies. However, our models could be extended and tested with other interesting latent and observable variables (eg. environmental concern, existing infrastructure) that may interact with the motivations and habits in defining the intentions. The models tested in this article are applied to data from mobility behaviours in the Grenoble region, which presents a certain number of specificities in terms of the deployment of transport infrastructures, in particular bicycle paths, and physical activity practices. It would be useful to replicate these models in other urban contexts, with populations with different socio-demographic characteristics. Lastly, our study was conducted in 2019 before the COVID-19 world pandemic. This external shock has demonstrated a significant effect on changing the transportation behaviour (Campisi et al., 2020; Kalter et al., 2021). However, less is known about the long term effect of the pandemic and whether these changes are long lasting. Thus, making a comparative study with post-pandemic data should be conducted to assess our model and compare its validity before and after this crisis.

Notes

[1]Policies to increase physical activity: https://www.who.int/news-room/fact-sheets/detail/physical-activity

[2]We describe the level of mobility of the observed individuals using their occupations. We suppose that an individual is "mobile" in case he has a professional activity or he is, a pupil, a student or an unpaid trainee. We assume that such categories of people will probably make a high number of trips to go to work or to study, etc. In parallel, we suppose that an individual is "less mobile" if he is unemployed, retired or pre-retired, a housekeeper or man and in any other inactive situation.

[3]Qualité de l'air dans l'agglomération grenobloise: Evaluation de l'environnement, du comportement et de la santé. The project was funded by Ademe (Agence de la transition écologique) and the Metro (Grenoble-Alpes Métropole)

[4]The survey allowed collecting data of 1,304 participants among which 271 are amotivated. These participants are discarded from our analyses since amotivated individuals are supposed to have null intentions while intentions is the dependent variable in the tested model.

[5]Following the results of the tests of normality of data Shapiro–Wilk (Shapiro and Wilk, 1965)

[6]A modification index is the χ value, with 1 degree of freedom, by which model fit would improve if a path was added or eliminated from a path model. Usually, values larger than 10 could be followed. However, adding these paths should not be justified only by the high level of the modification index but also theoretically supported.

CRediT author contribution statement:
Rim Rejeb: Conceptualization, Methodology, Formal analysis, Writing - Original Draft, Visualization, Writing - Review Editing. **Hélène Bouscasse:** Conceptualization, Validation, Writing - Review Editing. **Aïna Chalabaev:** Conceptualization, Validation. **Sandrine Mathy:** Conceptualization, Resources, Writing - Review Editing, Supervision.

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

Data availability:
The data that has been used is confidential

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Appendix: Detail of the Exploratory factor analyses

Carrying out an EFA allows us to validate scales of items in a questionnaire and derive a construct (e.g. Habits) for a group of items (e.g. Q2 to Q14). This statistical technique is done following a number of steps (Samuels, 2017).

We start by doing a serious of tests verifying the adequacy of doing an EFA on our data. First, factor analyses is based on the correlation matrix of the studied items. We find that the bi-variate correlation scores of these items are all below 0.8. Field (2013) suggests removing items that exceed this level of correlation.

Second, we check the Kaiser-Meyer-Olkin measure of sampling adequacy (KMO-test) verifying the adequacy of the sample size. We have a KMO above 0.8, more than the required 0.5 (Kaiser, 1974). We also apply the Bartlett's test of sphericity (Bartlett, 1950) testing the hypothesis H_0 that the correlation matrix is an identity matrix. The test is found significant at 5% level meaning that we could reject H_0. Lastly, the determinant of the correlation matrix is equal to $0.01 > 0.00001$ (Field, 2013) meaning that we do not have a multicollinearity problem.

The results of all these tests allow us to conclude that with our data we can perform an EFA.

We identify 3 factors with an Eigenvalue above 1 (known as Kaiser's stopping rule). The cumulative percentage of the variances of these factors is 60.04% which reaches just the recommended level for an EFA (Brown, 2009). A Varmax orthogonal rotation of our factors allowed us to better define the 3 factors that meet our theoretical model. Each factor is composed of a minimum of 4 items and has a factor loading above 0.4 (Samuels, 2017). We finish our EFA by verifying the internal consistency of the 3 identified latent constructs by calculating their Cronbach's alpha coefficients (α). For this test, a coefficient of 0.6 or above suggests a good level of internal consistency of the factor (Ursachi et al., 2015).

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