Determinants of smart energy tracking application use at the city level: Evidence from France*

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Abstract

This paper investigates the determinants of smart energy tracking app usage by citizens residing in French cities. Our framework is inspired by the extant strands of literature on smart cities and smart home technology adoption, but also contributing to them as smart energy applications reveal specificities that need to be incorporated; the latter include, for instance, the distinction between adoption and frequency of use, or the consideration of additional determinants such as privacy or environmental concerns. For our study, we build an original survey and rely upon citizen-level data, testing a Zero-Inflated Ordered Probit (ZIOP) model which allows to differentiate between adoption of the smart energy app and its frequency of utilisation. Our empirical findings reveal how the drivers related to smart city characteristics mainly affect the decision of adoption of energy tracking apps. Conversely, the more individual characteristics related to the perceived benefits of using energy tracking apps, dwelling type, and privacy concerns, primarily affect the frequency of utilisation. Our results bear policy implications on the issue of privacy, premising additional research on energy challenges in the utilization of energy apps in smart versus non-smart environments.

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1 Introduction

Since the beginning of the new century, the world population has been growing rapidly, with towns and cities accommodating half of this population and using 70% of available energy resources. The urban population is expected to rise to 70% by 2050 (UNCTAD, 2017[61]), and this creates a tremendous pressure on every aspect of the urban living. Within this context, technological solutions need to be developed in view of increasing energy efficiency and renewables, and this has triggered several smart city initiatives in Europe and outside of Europe (Wang and Moriarty, 2019[65]; Hall, 2000[27]; Caragliu et al., 2011[16]). In this regard, the smart cities literature has identified two main factors driving energy sustainability enhancement (Haarstad and Wathne, 2019[26]): the first refers to the technological aspect of smart energy solutions, whereas the second involves the level of social integration of such solutions among citizens. Despite the fact that most of the research has so far concentrated on the technological aspect (Calvillo et al., 2016[14]; Kramers et al., 2014[37]; Neirotti et al., 2014[45]), the social aspect has been lately acquiring more relevance in recent contributions (Bhati et al., 2017[11]; Mosannenzadeh et al., 2017[42]). Indeed, the development and implementation of smart city energy projects is not considered a sufficient condition *per se*; particularly, in order to achieve successful outcomes, technological solutions must be adopted and frequently utilized by citizens (Albino et al., 2015[5]; Mosannenzadeh et al., 2017[42]). This entails that, in order to achieve a successful outcome in the adoption and implementation of smart energy solutions, cities must place at the centre of their attention the needs and issues of citizens. In other words, citizens need to be informed and involved in smart energy initiatives, eventually acting as committed actors or co-creators.

Recent research in the field argues that smart cities need smart citizens, and here smartness of citizens is not solely captured by the level of education (Ashan and Haque, 2017[3]; Thompson, 2018[60]), but rather by the ability to use new digital services. This connects with a new strand of literature understanding and evaluating how Information and Communications Technology (ICT) usage such as Internet, smartphone applications (apps), Internet of Things (IoT) and data, might generate positive effects but also potential risks in individuals' well-being (Cecere et al., 2015[18]), thus encouraging or impeding adoption behaviours (Marikyan et al., 2019[40]; Bhati et al., 2017[11]; Baltan-Ozkhan et al., 2013a[7],b[8]; 2014; Mutargh et al., 2014[44]). In the context where smart homes and intelligent buildings are popping up, wireless sensors, remote monitoring and control systems are incorporated in dwellings to better optimize energy management based on monitoring key parameters by households (Paetz et al., 2012[48]; Shin et al., 2018[55]; Baudier et al., 2019[9]). In line with the increasing trend of considering user involvement and user learning abilities, "learning by looking" (Kendel et al., 2017[35]) represents a source of motivation enabling users to understand their daily energy consumption; in addition, it generates an increased visibility between citizens and the energy supplier based on consumer feedback, in view of potential reduction of household energy consumption.

Although the literature stresses that devices such as smart grids and meters have a positive impact on energy savings, there are still too few contributions focusing on the utilisation of smart apps for tracking energy consumption levels by domestic users. Smart energy apps are software applications for smartphones/tablets which can be downloaded by users and which allow them to monitor their real-time level of domestic energy consumption. Nowadays, there exist many different energy apps produced by different developers (such as Smappee, MeterPlug, EnergyCloud, Neurio, WiTenergy, etc.), each one with its own interface and possible additional options besides the standard energy monitoring, such as user alert in case of energy over-consumption, provision of energy tips, etc. (Geelen et al., 2019[23])[1]. To the best of our knowledge, the only contribution on the usage of smart energy apps is that one of Geelen et al. (2019)[23], who carried out a quasi-experiment in the Netherlands to assess whether the provision of a smart app monitoring system to a treatment group effectively led to energy savings compared to a non-treated group[2].

Our study focuses instead on the individuals' determinants of smart energy app utilisation, where we further distinguish between adoption and frequency of app usage. Our framework is inspired by the extant strands of literature on smart cities and smart home technology adoption, but it also contributes to them as smart energy applications reveal specificities that need to be incorporated. In particular, our paper is among the firsts investigating the linkage between privacy and adoption of energy friendly technologies. For our analysis, we build an original survey and rely upon citizen-level data, testing a Zero-Inflated Ordered Probit (ZIOP) model which allows to differentiate between adoption of the smart energy app and its frequency of utilisation. We use evidence from citizens in France living in two different city environments, with the opportunity to

[1]In practical terms, in order to operate the app, a user has to purchase a plug to connect directly to the electricity meter, which allows the sending of real-time energy consumption information to the app via a Wi-Fi/Bluetooth system. For a comprehensive technical explanation, see Keyhani, 2016[36].

[2]Although of interest, their results did not reveal a significant reduction in energy consumption among the two groups. In addition, this study suffers of some limitations, notably the lack of random assignment for the control-group, whose individuals resulted to be older and more educated compared to the national average.

compare citizen app usage in a smart *versus* non-smart city.

This study is finally motivated by the fact that in the current digital era, individual digital applications are increasingly downloaded (i.e., adopted) and used worldwide (i.e., with variable frequency), not only in relation to energy, but in many different fields (traffic, finance, weather, etc. (see Cao and Lin, 2017[15]), and, more recently, Covid prevention). Specifically, energy tracking apps allow citizens to be able to monitor their energy consumption level with an increased degree of visibility and user friendliness compared to other devices. Coping with the so called "energy invisibility" problem (Hargreaves et al., 2013[28]), energy tracking apps are then expected to help citizens in adapting in an efficient way their energy behaviour. The increased awareness of having a glance on energy consumption is also a way to fit the individual interest with the collective interest, since energy savings at the individual level are necessarily beneficial to the overall city. Exploring the usage of smart apps is thus a way to grasp how citizens become "smarter", i.e., more able to use sophisticated energy monitoring solutions for themselves while contributing to make the city as a whole more energy sustainable.

The rest of the paper is articulated as follows. Section 2 builds the theoretical framework on the utilisation of energy tracking apps drawing upon the latest contributions of the smart cities and smart home technology adoption literature. Section 3 develops the empirical strategy with the presentation of the data and methods of investigation. Section 4 discusses the empirical results. Finally, Section 5 concludes and delineates the contributions, limits and future research, as well as the policy implications deriving from our analysis.

2 Literature review and framework

Over the recent period, the smart cities literature and smart home technology adoption literature have shown a growing interest on the determinants of acceptance of smart home and intelligent building technologies and services adoption.

Following Marikyan et al., 2019[40], an avenue of research based on quantitative investigations in the user's perspective can be explored, providing new insights on the issues of adoption of smart home technologies in which we can position our framework. Several determinants have been identified in the empirical literature on smart home technology adoption, essentially consisting of four groups of benefit-related variables to which we refer. Due to the specificities of smart energy applications, we extend this set of determinants by further focusing on energy behavioural variables in the green context, which might play a role in adoption and frequency of use. In addition, we perform a deeper analysis of the role of privacy concerns inherent the adoption and use of smart apps. Then, we also review individuals' socio-demographic characteristics that might matter, together with type of dwelling and location. A comprehensive framework in the context of smart energy tracking apps is finally elaborated.

2.1 Smart home technology adoption and use: a definition

Smart home and intelligent building services have been defined according to characteristics such as technology, services, and the ability to satisfy users' needs (Marikyan et al., 2019[40]). Technology is defined as hardware and software components producing a variety of functions and services, taking the form of smart devices and sensors (De Silva et al., 2012[20]). These functions usually include assistance to residents from technologies that detect and gather multi-media information or home security monitoring, but they also include smart energy applications (energy tracking apps) that promote environmental sustainability (Bhati et al., 2017[11]). In this literature, however, adoption and use of smart energy applications have not been investigated explicitly. Indeed, the focus here is mainly on the benefits and risks related to smart home technologies as such, and especially on the knowledge that users have of the new technology, and how the ownership of other smart home technologies plays a role helping the use of this new technology (Wilson et al. 2017[69]). Interest can also be placed on users' awareness of what is a smart home technology, and their own perception of benefits and risks (Sanguinetti et al. 2018)[53]. In the extant adoption literature on smart home technologies, the aim is then to explain individuals' knowledge and benefits (or risk) perception, or alternatively, predicting individuals' adoption and use of IoT services (Shin et al. 2018[55])[3].

This definition is thus useful to our approach, but eventually needs to be amended for several reasons. First, we can only conjecture that smart apps in energy tracking are one type of smart home technologies, as this has not been investigated properly in the extant literature. Second, the extant literature mainly concentrated on the individuals' attitude towards an intention to adopt a smart home technology; however, this might be quite different from actual adoption, since our intention is primarily to explain observed individuals' adoption and frequency of use

[3] Shin et al. (2018)[55], e.g., developed a technology acceptance model (TAM). Specifically, they predicted the intention to adopt a smart home technology using a multivariate probit model to describe the use behaviour of the technology.

of energy tracking apps. According to Rogers (2003)[52], adoption occurs after the intention phase, when the decision to use a technology has already been made by the individual. Hence, adoption occurs when the individual purchases the technology; in our case, when the individual installs the mobile (energy) application on his/her smartphone/tablet. Furthermore, adoption is defined as the full use of an innovation, and differs from diffusion that is the process by which the innovation is communicated through certain channels over time among members of a social system (Rogers, 2003[52]). Third, in addition to adoption, smart energy apps further raise the issue of adopters' frequency of use, which is generally not considered in the literature, and this motivates the development of a two-stage framework which considers both the determinants of adoption (stage 1) and frequency of use (stage 2).

2.2 Benefit-related variables

The empirical literature in the field of smart home technology adoption has identified a group of determinants related to potential and perceived user benefits; namely: (i) environmental, (ii) social inclusion, (iii) financial/economic, and (iv) health-related. In short, two main triggers are at work: an extrinsic motivation (economic motivations, social pressures) and an intrinsic motivation (environmental issues, health related and well-being issues). These two forms of motivation could thus act on either the mere adoption or the continuous usage of the energy app. Tab. 1 outlines these determinants.

Health-related benefits are often discussed in the context of ageing population, vulnerable people and people with chronic disease conditions to be handled both inside and outside of the house (Karlin et al., 2015[34]). However, the relationship between adoption of smart technology apps and health concern has also been used in characterizing diverse groups of adopters (Sanguinetti et al., 2018[53]), suggesting a more systematic inclusion of health-related benefits in recent studies. More generally, health and well-being have been identified as potential triggers in the specific context of energy habits changes, as well as a critical issue producing potential behavioural lock in (Baum and Gross, 2017[10]; Welsh and Kühling, 2018[66]).

It has also been noted that the adoption of smart energy devices could be motivated by social influence. The latter mainly involves the influence exerted by the social sphere of individuals (*in primis*, family members, friends and acquaintances) on the adoption of smart home technologies[4].

[4]Family, friends and peers have indeed been proven to exert a notable influence on the behavioural choices of individuals, and especially in relation to previous experiences of the former on some specific issues (Babutsidze

Table 1: Potential and perceived user benefits of smart home adoption (Adapted from Marikyan et al. 2019[40], p.138).

Benefit	**Service**	**Immediate advantage**	**Long-term impact**
Environmental	Monitoring, consultancy, comfort	Energy optimization leading to positive environmental externalities	Environmental sustainability, reduction of carbon emissions
Social-related	Support	Social acceptance	Overcome the feeling of isolation
Economic / financial	Consultancy, monitoring	Reduction of energy bills	Economic gains and money saving
Health-related	Comfort, monitoring, consultancy, support deliver therapy	Interaction and feedback on medical prescriptions	Promote well-being of ageing and vulnerable people

This type of social pressure has been shown to be a critical variable in affecting both adoption and use (Venkatesh et al., 2012[63]). According to Balta-Ozkan et al. (2013a[7], 2013b[8]), adopting and using a smart technology at home seems to be positively impacted by social inclusion, since being included in a social group generally presents benefits.

Finally, in relation to environmental and economic benefits, a further distinction can then be made between citizens that are "device enthusiasts" (i.e., mostly interested in having a monitor to check their energy consumption) *versus* those who are truly "aspiring energy savings" to be materialized through the installation of devices at home (Urban and Scasny, 2012[62]). Environmental concerns and economic benefits seem to be of rather equal importance for "monitor enthusiast" citizens, whereas "aspiring energy savers" are mostly concerned environmentally (rather than economically) about how much energy they are using and how much energy they can save. This may suggest for this second category of citizens a stronger importance of environmental concerns in their motivations compared to the economic ones (Urban and Scasny, 2012[62]; Murtagh et al., 2014[44]).

2.3 Energy behavioural variables in the green context

When discussing households' energy behaviour in the green context, the literature generally refers to the growing threats of climate change, global warming, etc., and how controlling for energy usage helps with these issues (Balta-Ozkan et al., 2013a[7]). Within this framework, it is generally considered that the green context can help to explain citizens' use of energy efficient devices (Urban and Scasny, 2012[62]). Perri et al. (2020)[50] further showed how the environmental component has become a more significant factor influencing the adoption of smart energy solutions and virtuous energy behaviours by citizens, and notably in smart cities. In fact, citizens' adoption and usage of energy efficient devices promoting efficient energy behaviours represent one key objective in smart cities projects; in this regard, a distinction is usually made in the literature between "energy efficiency" and "energy curtailment" behaviours (see Gardner and Stern, 1996[22]). Specifically, energy efficiency behaviours refer to all those actions dedicated to the replacement and/or improvement of old inefficient energy devices with newer, more efficient ones. On the other hand, energy curtailment behaviours refer to virtuous behaviours on energetic issues adopted by individuals.

and Cowan, 2014[6]). Within our context, this implies that individuals' actions do not only follow the well-known contagion model of technological adoption, as depicted in Rogers (2003)[52], but their behaviour in smart app usage may also be affected by direct social interactions within their social circle.

Therefore, energy efficiency behaviours capture all those actions which rather involve the technological aspect of energy issues (e.g., the substitution of standard bulbs with energy-efficient LED bulbs), whereas energy curtailment behaviours rather involve the adoption of an energy-friendly conduct by individuals over time (e.g., turning off the heating system when not in the house). Both these two types of energy behaviours have been reputed to exert a notable impact on the decision to adopt smart energy solutions in recent studies (Testa et al., 2016[58]).

2.4 Privacy concerns

It is commonly accepted in the smart home technology literature that personal data protection represents one of the most important disadvantages related to these technologies (Wilson et al. 2017[69]; Marikyan et al., 2019[40]). Threats to the system security and potential invasion of home residents privacy have been pointed out as recurring concerns for potential adopters and users of such technologies (Balta-Ozkan et al., 2013a[7], 2013b[8]). In this regard, individuals may not feel comfortable with the great deal of sensitive personal data (including data related to day-to-day activities) which a smart home technology can collect and store. However, findings in the literature seem to be unclear about individuals' privacy concerns. Defined as the ability of consumers to control the terms under which personal information is acquired and used (Westin, 1967[67]), privacy is highlighted as an antecedent to the adoption of mobile services (Chellapa and Sin, 2005[19]) and any online service requiring personal information (Lancelot-Miltgen et al., 2013[38]; Cecere at al., 2015[18]). With reference to online privacy concerns, previous works have detected mixed results in the social network services adoption literature. Cecere at al. (2015)[18] found that the latter have a negative impact on behavioural intentions to adopt or to use an ICT service.

In the specific context of smart home technologies, some authors found that the opinion of smart home technology adopters are split between those who embrace the benefits of the technology without being bothered by privacy issues, and those who fear security threats when home automation and remote control are disclosed and used by third parties (Marikyan et al., 2019[40]). Other authors showed that privacy issues appear prevalent for all smart technology adopters (Sanguinetti et al., 2018[53]). Conversely, Gerpott and Paukert (2013)[24] detected how households in Germany do not perceive, on average, any risk related to privacy violation. Some authors finally argue that the inconsistency already identified in the general ICT acceptance literature is also valid in the context of smart home technologies. For example, Shin et al. (2018)[55] showed that privacy concerns have no significant effect on attitude towards smart home technologies, but remain a factor encouraging people to postpone their purchases. However, there is no literature documenting that such inconsistency is also present in relation with use. In fact, this involves further investigation, since the role of privacy concerns appears not to play the same effect depending on the type of smart home technology considered and age of the respondents surveyed. For example, Balta-Otzkan et al. (2013a)[7] showed that old people perceive monitoring as part of smart health services that would be too much intrusive, while services such as alerting a carer if problems were detected are generally viewed more positively. The same study also showed how younger people are keen to believe that health services have the potential to invade privacy.

More generally, as shown in the privacy concerns literature, the effect of socio-demographic variables (age, gender, and education in particular) is not always clear. Several studies on social network services found a positive association between age and education in relation to privacy concerns. For example, Cecere et al. (2015)[18] found that highly educated individuals are more concerned about the online disclosure of personal information. At the same time, the effect of gender remains less clear; indeed, while some studies assert that men are less concerned than women over the online disclosure of their personal information (Acquisti and Gross, 2006[2]; Cecere et al., 2015[18]), others have found that the opposite is true (Jensen et al., 2005[33]), or detected no gender differences in the perception of privacy (Yao et al., 2007[73]). Ultimately, all these blocks of the privacy concerns literature lead us to assume that individuals' privacy concerns may impact significantly the probability of a citizen to adopt and use an energy app.

2.5 Socio-demographic, location and dwelling variables

The smart home technology adoption literature also considers the role of socio-demographic characteristics. Nonetheless, results of previous studies are not clear about the role exerted by determinants such as education and gender. In Baudier et al. (2019)[9], for example, the impact exerted by education provides mixed results, and the same applies when considering the gender variable. Always with reference to the gender variable, Karlin et al. (2015)[34] detected how men are more likely to adopt a smart home technology, whereas Parag and Butbul (2018)[49] found the opposite. When considering the age variable, as reported in Parag and Butbul (2018)[49], the latter is generally negatively correlated with adoption behaviour; for instance, Michaels and Parag (2016)[41] detected that people under the age of 45 are more prone to adopt innovative smart home technologies compared to older people, due to a higher degree of familiarity with technology.

Another important factor explaining smart app adoption is represented by dwelling type. Yet, mixed results emerge in the literature about this factor. Balta-Ozkan et al. (2013a[7]), for instance, found how the latter has been identified as significantly influencing citizens' attitudes to adopt or use a smart technology. On the other hand, according to Sanguinetti et al. (2018)[53], being an owner, rather than a tenant, does not seem to impact significantly on smart home technology adoption.

Finally, when comparing different studies in the smart cities literature, most of them found how the presence of a smart urban environment produces a positive effect on the adoption of smart home technologies by citizens. Indeed, smart factors such as the presence of supporting urban technological policies, an efficient urban governance, and integrated decision-making processes among the actors involved, have generally proven to catalyze the adoption of smart technological solutions by citizens (Wang and Moriarty, 2019[65]; Haarstad, 2016[25]). Nonetheless, a few contributions have found how the presence of a smart urban environment may also reduce, in some cases, the same adoption of smart technologies (Yigitcanlar, 2016[74]).

2.6 Summing up

Based upon the strands of literature discussed above, we can now elaborate our theoretical framework to investigate the determinants of smart app usage, considering both adoption and frequency of use as key steps in our analysis. The set of variables we thus consider in our framework are: the benefits related to smart home technology adoption and use (environmental, social pressure, economic, and health), energy behavioural variables in the green context (namely, energy curtailment and energy efficiency behaviours), privacy concerns, socio-demographic characteristics (age, gender, and education), dwelling type (owner *versus* tenant), and location (smart *versus* non-smart urban environment). Fig. 1 summarizes our theoretical framework structuring the paper.

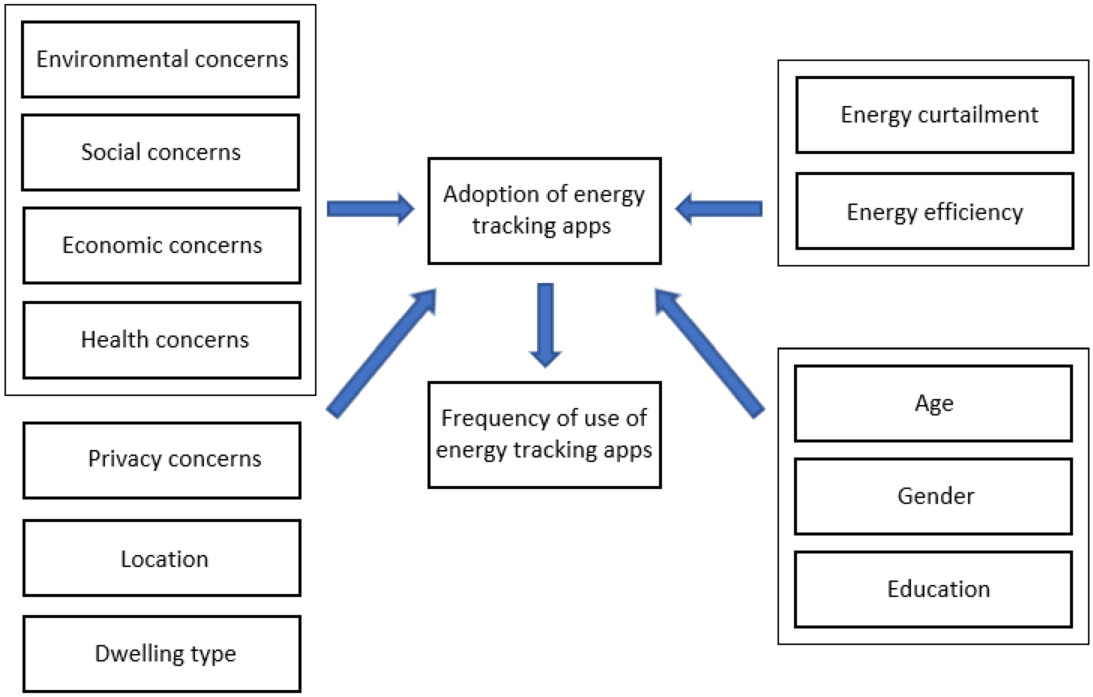

Figure 1: Theoretical framework.

3 Data and Methodology

In this section, we present the data we have collected and the methodology adopted to analyse the data.

3.1 Data

Our study focuses on citizens living in two French cities, Nice and Bordeaux, which have been chosen as representative of smart *versus* non-smart environments for citizens. According to international smart city rankings such as the CIMI Smart City ranking[5], in 2018 Nice positioned in the top 80 smart cities in the world, and the second in France (just after Paris). Since the early 2000s, sophisticated technological solutions in the energy field were developed in conjunction with

[5]The CIMI (Cities In Motion Index) is produced every year, and it is considered amongst the most reputed smart city indexes used worldwide. The computation of the rank to provide to a city the status of "smart" considers several aspects, such as technological, economic and urban characteristics (for a more thorough review, see: https://media.iese.edu/research/pdfs/ST-0471-E.pdf).

proactive and efficient policy measures supported by different programmes (EU H2020 project IRIS Smart Cities; EU FP7 projects like INTERFACE, CITYOPT, GRID4EU; or FLEXGRID at the regional level). The latter contributed at promoting energy savings among residents and increased energy efficiency in public facilities. Concrete examples of implemented smart solutions which effectively led to domestic energy optimization have been involving: positive energy buildings, symbiotic waste heat networks, flexible electricity grid networks, and smart multi-sourced low temperature district heating with innovative storage solutions (IRIS D6.1, 2018[32]; IRIS D6.2, 2018[31]). In addition, a considerable effort was put by local authorities to incentivize residents in pursuing efficient energy behaviours through targeted awareness campaigns. Ultimately, all these actions have proven to be successful in achieving positive energy outcomes, notably with respect to domestic energy savings. As it was stressed above, the smart cities literature has demonstrated how smart urban environments generally exert a significant impact on the adoption of smart energy solutions by citizens. In the light of this, we may expect a different attitude towards the adoption and use of energy apps for residents of Nice with respect to residents of a city which was not (or only limitedly) affected by the implementation of similar smart solutions (/actions); within this context, the city of Bordeaux represents a valuable example, as the latter does not appear listed in the CIMI Smart City ranking or in any other comparable international ranking. In addition, it shares common characteristics with Nice, such as city size and population.

For the analysis, we elaborated an original survey to collect data from citizens in April 2018 following a quota sampling method. Specifically, we circulated an online questionnaire to a random sample of 500 individuals aged 18 and older living in Nice and 501 individuals living in Bordeaux, for a total of 1001 individual cross-sectional units. This survey was conducted for a period of three weeks, and the questions asked aimed to investigate the set of determinants of our theoretical framework affecting energy tracking app adoption and frequency of utilisation. The questions were elaborated drawing upon the relevant theory on smart cities and technology adoption discussed in the previous section[6]. The variables derived from the questions are either categorical, ordinal or discrete (Tab. 2). Ordinal variables derive from the following choices: "Never", "Rarely", "Often", "Very often", assigning to the latter a value of 0,1,2, and 3, respectively. As stressed, our survey differs from previous investigations by focusing not only on adoption, but also on the frequency of use, in order to have a better and more refined understanding of the impact exerted

[6]In elaborating the survey, we developed clear and brief questions embedded into a user friendly layout. In addition, we refrained from asking about sensitive information such as income or health status. This strategy allowed us to minimize drastically the number of incomplete responses.

by each determinant on smart app usage. Specifically, our outcome variable is derived from the question "How often do you use smart apps to track your level of energy consumption at home?"[7], where the "Never" response includes the set of non-adopters, whereas the responses associated to "Rarely", "Often", "Very often" include the set of app adopters, with the relative frequencies of app utilisation.

Descriptive statistics for our response variable and the set of determinants are reported in Tab. 2. From the table, it appears how the share of individuals utilizing energy apps at a high frequency rate is not considerable. In addition, it is also possible to observe a slightly higher percentage of male respondents and tenants when considering the gender and dwelling type variables, respectively. Then, the mean for the age variable results to be 46 years, whereas for the variable capturing the years of education is 13 years. With reference to environmental and economic sensitivity, slightly more than half of respondents claim not to be concerned by these issues in affecting their energy behaviour. On the other hand, the percentage of respondents not concerned by health issues results to be remarkably pronounced. Regarding social concern, it appears that slightly more than one third of respondents is often solicited by family members in adopting virtuous environmental choices. With reference to privacy issues, it emerges how around two thirds of respondents is never or rarely worried about privacy concerns, but the remaining share of respondents seems conversely to be concerned often or very often. Then, around 70% of respondents is used to turn off the heating system very often when leaving the house; conversely, the share of respondents who unplug unutilized devices often or very often, slightly falls behind the share of respondents who do unplug never of rarely. Finally, most respondents utilize LED bulbs often or very often.

In order to provide a preliminary insight on the degree of pairwise correlation among the variables, we additionally report in Tab. 3 a correlation matrix based on the Spearman's rank correlation coefficient. From Tab. 3, significant levels of correlation emerge between the dependent variable and most of the independent variables. In addition, environmental sensitivity seems to be positively correlated to both energy efficiency and curtailment habits (but not with the variable Heating), whereas mixed results emerge when comparing the pairwise level of association between the different benefit-related variables. At the same time, individuals with a higher privacy concern also seem to pair with a higher degree of environmental sensitivity and social inclusion. Finally, the positive correlation between health benefits and the location of users based in Nice might be

[7]The question refers to the usage of any generic smart app allowing the monitoring of domestic energy consumption.

Table 2: Descriptive statistics.

Variable	*Type*	*Label*	*Mean (or %)*	*Std.dev.*	*Min*	*Max*
Usage of smart energy apps	Ordinal	How often do you use smart apps to track your level of energy consumption at home?	Never = 0 (46%), Rarely = 1 (43%), Often = 2 (3%), Very often = 3 (8%)	-	0	3
Dwelling	Categorical	Owner or tenant?	Owner = 1 (45%), tenant = 0 (55%)	-	0	1
Gender	Categorical	Male or female?	Male = 1 (51%), female = 0 (49%)	-	0	1
Age	Discrete	Age?	Mean = 46 years	19.3	18	95
Education	Discrete	Years of education?	Mean = 13 years	3.1	5	16
Location	Categorical	City of residence?	Nice = 1 (50%), Bordeaux = 0 (50%)	-	0	1
Environment	Categorical	Do carbon footprint issues affect your energy habits change?	Yes = 1 (48%), No = 0 (52%)	-	0	1
Economic	Categorical	Do economic reasons affect your energy habits change?	Yes = 1 (45%), No = 0 (55%)	-	0	1
Health	Categorical	Do health reasons affect your energy habits change?	Yes = 1 (18%), No = 0 (82%)	-	0	1
Social	Ordinal	Does social pressure (by family members / friends) affect your energy habits change?	Never = 0 (36%), Rarely = 1 (25%), Often = 2 (36%), Very often = 3 (3%)	-	0	3
Privacy	Ordinal	Are you concerned with the collection of your personal data when you use a smart application?	Never = 0 (23%), Rarely = 1 (40%), Often = 2 (22%), Very often = 3 (15%)	-	0	3
Heating	Ordinal	Do you turn off the heating when leaving the house?	Never = 0 (19%), Rarely = 1 (3%), Often = 2 (7%), Very often = 3 (71%)	-	0	3
Unplug	Ordinal	Do you unplug inutilized energy devices?	Never = 0 (34%), Rarely = 1 (24%), Often = 2 (19%), Very often = 3 (23%)	-	0	3
LED	Ordinal	Do you use low-energy LED bulbs?	Never = 0 (10%), Rarely = 1 (7%), Often = 2 (22%), Very often = 3 (61%)	-	0	3

simply the reflex of an older population compared to the city of Bordeaux; in a similar fashion, the positive correlation between the location of users based in Nice and dwelling type can be explained by a higher number of owners in the city of Nice compared to Bordeaux.

3.2 Methodology

In the literature, different methodological options to analyse survey-level data are present. In our case, since we are dealing with non-negative integer data displaying a significant amount of zeros, one of the most straightforward approaches we can utilize to frame individuals' behaviour is represented by a two-part (or hurdle) model; the latter allows to overcome the limitation imposed by the standard Tobit model in corner solution applications assuming a single data generating process for both zero and positive observations (Woolridge, 2010[71]). Specifically, the two-part model sets in the first stage a binary model which determines a zero or non-zero outcome, depending, respectively, on whether an individual chooses between not to install or to install the app. In the latter case, the "hurdle is crossed" and thus, conditional on the fact of having installed the app, the frequency of utilisation is subsequently modeled in the second stage by a model for positive integer count data (usually a Poisson or negative binomial model). Due to its appealing assumptions in describing individuals' behaviour, the two part model has been used extensively in various strands of the applied econometric literature to frame survey data splitting between choice and frequency decisions of individuals; notable examples include: doctor visits (Van Ophem, 2011[47]; Winkelmann, 2004[70]), expenditure on financial assets (Brown et al., 2015 [13]), etc. In addition, the usage of two-part models represents a better alternative to standard Poisson and negative binomial models for count data in the presence of excesses of zeros (Zhang et al., 2018[75]).

In light of these premises, we firstly set a two-part model as the initial framework for our case study, in order to have an understanding of the impact exerted by each determinant on the adoption and frequency of utilisation of energy tracking apps. Therefore, a probit regime equation is introduced in the first stage to define the binary choice of an individual to install or not to install the app; then, a Poisson model is used in the second (outcome) stage to capture the frequency of utilisation of the same app by the same individual. Thus, denote in the first stage equation as q_i^* the latent variable of a standard probit model expressing the probability of installation choice by the individual i, where we observe $q_i = 1$ in case of installation and $q_i = 0$ in case of non-installation. The mapping between q_i^* and q_i can hence be defined as:

Table 3: Spearman's correlation coefficient matrix.

Variables	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. App usage	1													
2. Environment	0.1275**	1												
3. Social	0.0747**	0.1570***	1											
4. Economic	0.0699**	-0.1367***	-0.0482	1										
5. Health	0.0495	0.0493	0.0051	-0.4272***	1									
6. Privacy	0.1228**	0.0842**	0.0973**	-0.0262	0.0096	1								
7. Location	-0.0155	-0.0350	-0.1022**	-0.0854**	0.0706**	0.0247	1							
8. Dwelling	-0.1236**	-0.0281	0.0849**	-0.0319	-0.0431	-0.0279	0.1434***	1						
9. Unplug	0.0953**	0.1723***	0.0497	-0.0828**	0.0024	0.1408***	-0.0457	-0.0374	1					
10. Heating	0.0731**	-0.0285	0.0605	0.0960**	-0.0815**	0.0233	-0.1361***	0.0560*	0.0603*	1				
11. LED	0.0699**	0.0947**	0.0136	0.0016	-0.0351	-0.0442	-0.0224	0.1039**	0.1096**	0.0463	1			
12. Age	-0.1181**	0.0292	0.1068**	-0.0929**	0.0563*	-0.0943**	0.1665***	0.4823***	0.0421	-0.0844**	0.2302***	1		
13. Gender	-0.0063	-0.0384	0.0481	0.0209	-0.0582*	-0.0396	-0.0070	-0.0314	-0.0988**	-0.0383	-0.0399	-0.0240	1	
14. Education	0.0226	-0.0353	0.1480***	0.0665**	-0.1417***	0.0587*	-0.1458***	0.1221**	-0.0188	0.1650***	0.0459	-0.0816**	0.0558*	1

Note: Levels of significance: **p<0.10*, ***p<0.05*, and ****p<0.01*.

$$q_i^* = \boldsymbol{x'_i \alpha} + \nu_i, \qquad q_i = \begin{cases} 1 & \text{if} \quad -\nu_i < \boldsymbol{x'_i\alpha} \\ 0 & \text{if} \quad -\nu_i \geq \boldsymbol{x'_i\alpha} \end{cases} \tag{1}$$

where $\boldsymbol{x'_i}$ and $\boldsymbol{\alpha}$ are, respectively, the vectors of the covariates affecting app installation choice and the related coefficients, and ν_i is the normally distributed error term. From Eq. 1, the probability of installing the app is thus given by: $Pr(q_i = 1|\boldsymbol{x_i}) = Pr(q_i^* > 0|\boldsymbol{x_i}) = \Phi(\boldsymbol{x'_i\alpha})$, whereas the probability of non-installing the app: $Pr(q_i = 0|\boldsymbol{x_i}) = Pr(q_i^* \leq 0|\boldsymbol{x_i}) = 1 - \Phi(\boldsymbol{x'_i\alpha})$, where $\Phi(.)$ is the normal cumulative distribution function.

Subsequently, conditional on the fact that the individual i has installed the app (i.e., $q_i = 1$), a zero-truncated Poisson model is utilized to measure the frequency of utilisation $\bar{\bar{y}}_i$; thus:

$$\bar{\bar{y}}_i = \Phi(\boldsymbol{x'_i\alpha}) \frac{e^{-e^{\boldsymbol{z'_i\gamma}}} e^{\boldsymbol{y'_i z'_i \gamma}}}{(1 - e^{-e^{\boldsymbol{z'_i\gamma}}})\boldsymbol{y'_i}!}, \; (q_i = 1) \tag{2}$$

where $\boldsymbol{z'_i}$ and $\boldsymbol{\gamma}$ are, respectively, the vectors for the covariates affecting the app usage and the related coefficients, derived by modelling the mean of the predicted distribution with the log link function $\lambda_i = e^{\boldsymbol{z'_i\gamma}}$, and $\boldsymbol{y'_i}$ is the vector for the observed app utilisation frequencies. Then, in modelling the mass function of the binary model with a log-log link function, we can write $\Phi(\boldsymbol{x'_i\alpha}) = e^{-e^{\boldsymbol{x'_i\alpha}}}$. Defining in the parameter space $\boldsymbol{\Psi}$ the vector of parameters $\boldsymbol{\psi} = [\boldsymbol{\alpha'}, \boldsymbol{\gamma'}]'$ for the sample of $i = 1, ..., 1001$ individuals, the log-likelihood function for the hurdle model to be maximized can hence be written as:

$$\max_{\psi \epsilon \boldsymbol{\Psi}} \Big\{ \sum_{i \in \Omega_0} \ln(1 - e^{-e^{\boldsymbol{x'_i\alpha}}}) + \sum_{i \in \Omega_1} - e^{\boldsymbol{x'_i\alpha}} - \sum_{i \in \Omega_1} e^{\boldsymbol{z'_i\gamma}} + \sum_{i \in \Omega_1} \boldsymbol{y'_i z'_i} \gamma - \sum_{i \in \Omega_1} \ln[(1 - e^{e^{\boldsymbol{z'_i\gamma}}})\boldsymbol{y'_i}!] \Big\} \tag{3}$$

Where $\Omega_0 = \{i|\bar{\bar{y}}_i = 0\}$ and $\Omega_1 = \{i|\bar{\bar{y}}_i \neq 0\}$ are the two complementary sets for the sample of individuals (i.e., $\Omega_0 \bigcup \Omega_1 = \{1, 2, ..., 1001\}$). If the two sets of covariates $\boldsymbol{x'_i}$ and $\boldsymbol{z'_i}$ are distinct, the computation of the marginal effects is simply obtained by differentiating with respect to the two sets of variables separately. For variables appearing both in $\boldsymbol{x'_i}$ and $\boldsymbol{z'_i}$, the effects are added.

The full set of probabilities for the hurdle model can be summarized as follows:

$$\begin{aligned} Pr(y) &= \begin{cases} Pr(y = 0|\boldsymbol{x_i}) = Pr(q = 0|\boldsymbol{x_i}) \\ Pr(y = j|\boldsymbol{z_i}, \boldsymbol{x_i}) = Pr(q = 1|\boldsymbol{x_i}) Pr(y_i = j|\boldsymbol{z_i}, q = 1) \end{cases} \\ &= \begin{cases} Pr(y = 0|\boldsymbol{z_i}, \boldsymbol{x_i}) = 1 - \Phi(\boldsymbol{x'_i\alpha}) \\ Pr(y = j|\boldsymbol{z_i}, \boldsymbol{x_i}) = \Phi(\boldsymbol{x'_i\alpha}) f(.) \end{cases} \end{aligned}$$

where $f(.) = \frac{e^{-\lambda_i}\lambda_i^j}{(1-e^{-\lambda_i})j!}$, with $j = \{1, 2, 3\}$ denoting the positive frequencies of utilisation. Despite its desirable properties, the two-part model has two main limitations. Firstly, it is better designed for unordered count data, whereas in our case we have an ordered categorical response variable. Secondly, the two-part model assumes that there is only one process by which a zero can be produced, which is related to the choice made by an individual whether to install or not install the app, and in case the former option is chosen, the frequency of utilisation only takes positive values. Nonetheless, in reality, it is often the case that the emergence of a zero value in the outcome variable may derive not only from the decision to not install the app, but it might also emerge when an individual chooses to install the app, but then he/she does not use it. In such a case, the appearance of zeros in the response variable is inflated, since it derives from two different data generating processes; that is, a zero response in the usage of the app can include both genuine non-users (which decide not to install the app *in omni circumstantia*) and individuals who even if they installed the app they do not use it, but would do so under certain conditions. As a result, zero-inflated models have been developed to specifically account for this peculiarity (Hu, 2011[30]). Among such models, the zero-inflated ordered probit model (ZIOP) for ordered response variables developed by Harris and Zhao (2007)[29] represents the best model specification for our specific case, due to the ordered nature of our outcome variable. We will now show how the zero-inflated ordered probit model frames in our case study.

The ZIOP model is composed of two latent equations in two consequential stages: a probit regime equation in the first stage, which defines the binary choice of an individual to install the app, and an ordered probit outcome equation in the second stage, which captures the frequency of utilisation of the same app by the user. The setting of the probit regime equation is identical to the one identified in Eq. 1 for the two-part model; thus, also in the ZIOP, we have the latent variable q_i^* expressing the installation choice by the individual i in the first stage equation, which is observed in the binary form for $q_i = 1$ in case of installation and $q_i = 0$ in case of non-installation. Subsequently, conditional on $q_i = 1$, denote as y_i^* the latent variable expressing the frequency of utilisation of the app by the individual i in the second stage equation, which is observed in the discrete ordinal variable $\tilde{y}_i$, and can hence be framed by a standard ordered probit model:

$$y_i^* = \boldsymbol{z'_i\gamma} + \eta_i,\ (q_i = 1), \qquad \tilde{y}_i = \begin{cases} 0 & \text{if} \quad y_i^* \leq 0 \\ 1 & \text{if} \quad 0 < y_i^* \leq \mu_1 \\ 2 & \text{if} \quad \mu_1 < y_i^* \leq \mu_2 \\ 3 & \text{if} \quad y_i^* \leq \mu_3 \end{cases} \tag{4}$$

where η_i is the normally distributed error term. As in the two-part model, different sets of variables could drive the decisions of app installation ($\boldsymbol{x'_i}$) and utilisation ($\boldsymbol{z'_i}$).

As mentioned above, the main difference between the zero-inflated model and the two-part model relies upon the data generating process for the emergence of zeros in the data. Indeed, differently from the two-part model, the ZIOP model entails two distinct processes which can produce a zero, since the choice of installing the app and its frequency of utilisation are considered jointly. In fact, a zero value in the outcome equation may either derive from the choice made by a user not to install the app (i.e., when $q_i = 0$), or when an individual chooses to install the app, but then he/she does not use it (i.e., when $q_i = 1$ and $y_i^* \leq 0$). In light of this, the full set of probabilities for the ZIOP model can be summarized as follows:

$$\begin{aligned} Pr(y) &= \begin{cases} Pr(y=0|\boldsymbol{z_i},\boldsymbol{x_i}) = Pr(q=0|\boldsymbol{x_i}) + Pr(q=1|\boldsymbol{x_i})Pr(y_i=0|\boldsymbol{z_i},q=1) \\ Pr(y=j|\boldsymbol{z_i},\boldsymbol{x_i}) = Pr(q=1|\boldsymbol{x_i})Pr(y_i=j|\boldsymbol{z_i},q=1) \end{cases} \\ &= \begin{cases} Pr(y=0|\boldsymbol{z_i},\boldsymbol{x_i}) = [1-\Phi(\boldsymbol{x'_i\alpha})] + \Phi(\boldsymbol{x'_i\alpha})\Phi(-\boldsymbol{z'_i}\gamma) \\ Pr(y=j|\boldsymbol{z_i},\boldsymbol{x_i}) = \Phi(\boldsymbol{x'_i\alpha})[\Phi(\mu_j - \boldsymbol{z'_i}\gamma) - \Phi(\mu_{j-1} - \boldsymbol{z'_i}\gamma)] \end{cases} \end{aligned}$$

In this framework, the inflation of zero observations thus stems from the combination of probabilities of no app installation from the binary model, and of no utilisation from the ordered probit model. Conversely, a positive value in the frequency of the app utilisation is conditional on the fact that a user decides *a priori* to install the app. As in the two-part model, the two sets of covariates in the ZIOP model affecting the regime and outcome equations (respectively $\boldsymbol{x'_i}$ and $\boldsymbol{z'_i}$) do not necessarily have to coincide. In our case, all the determinants of energy tracking app usage enter both in the regime and outcome equations, since we want to analyze the impact exerted by these factors on both the adoption and frequency of utilisation of smart apps. The error terms of the regime and outcome equations (ν_i and η_i) may further denote correlation; supposing that the latter follow a bivariate normal distribution, the correlation among decisions can be expressed as:

$$\begin{bmatrix} \eta \\ \nu \end{bmatrix} \overset{i.i.d.}{\sim} \mathcal{N}\left(\begin{matrix} 0 \\ 0 \end{matrix}, \begin{bmatrix} \sigma_\eta^2 & \rho\sigma_\eta\sigma_\nu \\ \rho\sigma_\eta\sigma_\nu & \sigma_\nu^2 \end{bmatrix} \right)$$

where σ_η and σ_ν are the variances of η and ν respectively, and ρ is the scalar coefficient measuring the strength of the correlation between η_i and ν_i. For a value of ρ significantly different from zero, the ZIOP becomes a zero-inflated ordered probit model with correlated disturbances

(ZIOPC), which allows for a more accurate derivation of the estimates. Defining in the parameter space $\mathbf{\Theta}$ the vector of parameters $\boldsymbol{\theta} = [\boldsymbol{\alpha'}, \boldsymbol{\gamma'}, \boldsymbol{\mu'}, \rho]'$ for the sample of $i = 1, ..., 1001$ individuals, the log-likelihood function for the ZIOP(C) to be maximized can be written as:

$$\max_{\theta \epsilon \mathbf{\Theta}} \sum_{i=1}^{1001} \sum_{j=0}^{3} \mathbf{1}_{ij} \ln[\Pr(y_t = j | \boldsymbol{x'_i}, \boldsymbol{z'_i}, \theta)] \tag{5}$$

where $\mathbf{1}_{ij}$ is an indicator function such that $\mathbf{1}_{ij} = 1$ if $y_i = j$, and $\mathbf{1}_{ij} = 0$ otherwise. Subsequently, as in non-linear probit and ordered probit models, the precise impact of each explanatory variable on the probability of each discrete outcome j is computed through marginal effects. In case of a standard ordered probit model, the marginal effect would be computed as follows:

$$\underset{\Pr(y=j)}{ME} = \frac{\partial \Pr(y=j)}{\partial \boldsymbol{z}} = \left[\Phi\left(\mu_{j-1} - \boldsymbol{z'_i}\gamma\right) - \Phi\left(\mu_j - \boldsymbol{z'_i}\gamma\right)\right] \boldsymbol{\gamma} \tag{6}$$

Conversely, in the ZIOP(C) model, as in the two-part model, the marginal effects have to take into account the fact that different variables can enter in both the regime and outcome equations. Therefore, denote as α^* and γ^* the coefficient vectors associated to the explanatory variables for the whole model (i.e., variables appearing in one of the two equations and in both). The marginal effect for the ZIOP(C) model can hence be written as:

$$\begin{aligned} \underset{\Pr(y=j)}{ME} = \Phi\left(\frac{\boldsymbol{z'_i}\boldsymbol{\gamma} - \mu_{j-1} - \rho \boldsymbol{x'_i}\boldsymbol{\alpha}}{\sqrt{1-\rho^2}}\right) \Phi(\boldsymbol{x'_i}\boldsymbol{\alpha})\boldsymbol{\alpha^*} + \Phi(\boldsymbol{z'_i}\boldsymbol{\gamma} - \mu_{j-1}) \\ \times \left(\frac{\boldsymbol{x'_i}\boldsymbol{\alpha} - \rho(\boldsymbol{z'_i}\boldsymbol{\gamma} - \mu_{j-1})}{\sqrt{1-\rho^2}}\right) \boldsymbol{\gamma^*} \end{aligned} \tag{7}$$

4 Results

The marginal effects for the hurdle, ZIOP and ZIOPC models in relation to the probability of app installation are reported in Tab. 4[8]. The marginal effects for the hurdle, ordered probit, ZIOP and ZIOPC models for the frequency of app usage are reported in Tab. 5. Overall, from the two tables, the coefficient estimates remain rather stable across the hurdle and the zero inflated models, either when considering the regime and the outcome level[9]; conversely, the higher variation detected with respect to the ordered probit model provides evidence to consider the choices of app installation and frequency of utilisation as two separated processes. In addition, the Akaike information criteria denote a better performance for the zero inflated ordered models against the other models; this indicates the relevance of correcting for an excess of zeros in the dataset, suggesting as well the presence of two different generating processes for the emergence of responses related to no app usage. Thus, in the following discussion of results, the coefficient estimates for the ZIOPC model will be implicitly considered.

Benefits related to energy tracking app adoption and use

When considering the coefficient estimates related to the benefit-related variables, interesting results emerge. First, social influence has an effect on both the adoption and frequency of use. Furthermore, similarly to Balta-Ozkan et al. (2013a[7]), health concerns appear to exert a notable positive impact on the frequency of usage of energy tracking apps, but no significant impact is detected with reference to adoption. Then, when considering economic concerns, our results are in line with the findings of Murtagh et al. (2014)[44], and Balta-Ozkan et al. (2013b[8]), who found that urban citizens are remarkably motivated, in the degree of usage of smart technology, by economic benefits. In a similar fashion, environmental concerns also appear to significantly affect the intensity of use of the smart app rather than its adoption. Ultimately, benefit-related variables

[8] The interpretation of the magnitude for the marginal effects of the ZIOP and ZIOPC models follows the one of a standard probit (/ordered probit) model. For instance, when considering the zero-inflated models coefficient estimate for the age variable in Tab. 4, we have that individuals living in Nice are around 3% less likely to install smart energy apps compared to individuals living in Bordeaux.

[9] We further conduct a series of robustness checks to assess the stability of our coefficient estimates (see Appendix). Specifically, we re-estimate the ZIOP and ZIOPC models considering different sets of explanatory variables in function of class of belonging. The results obtained verify the stability of our coefficient estimates.

Table 4: Probability of app installation.

	Hurdle		ZIOP		ZIOPC	
	ME	Std. Err.	ME	Std. Err.	ME	Std. Err.
Benefit-related						
Environment	0.0101	0.0162	0.0055	0.0120	0.0041	0.0114
Social	0.0218**	0.0091	0.0143*	0.0079	0.0134*	0.0082
Economic	0.0398*	0.0176	0.0256	0.0175	0.0229	0.0174
Health	0.0269	0.0216	0.0172	0.0166	0.0147	0.0155
Privacy concerns						
Privacy	0.0205*	0.0089	0.0127	0.0079	0.0115	0.0083
Location and dwelling						
Location	-0.0445**	0.0167	-0.0321**	0.0121	-0.0314**	0.0117
Dwelling	0.0125	0.0185	0.0106	0.0142	0.0115	0.0140
Socio-demographic						
Age	-0.0024***	0.0005	-0.0016**	0.0007	-0.0016**	0.0007
Gender	0.0020	0.0164	0.0001	0.0116	-0.0008	0.0116
Education	0.0044	0.0026	0.0031	0.0019	0.0031	0.0019
Energy curtailment						
Unplug	0.0073	0.0070	0.0040	0.0053	0.0044	0.0055
Heating	0.0193**	0.0059	0.0128**	0.0051	0.0126**	0.0054
Energy efficiency						
LED	0.0090	0.0078	0.0058	0.0053	0.0047	0.0058
ρ					0.5013*	0.2743
AIC	2525.379		1935.329		1934.683	
N. observations	1001		1001		1001	

Note: Levels of significance: **p<0.10*, ***p<0.05*, and ****p<0.01*. Robust standard errors in parenthesis.

Table 5: Frequency of app usage.

	Hurdle		Ordered probit		ZIOP		ZIOPC	
	ME	Std. Err.	ME	Std. Err.	ME	Std. Err.	ME	Std. Err.
Benefit-related								
Environment	0.1444**	0.0450	0.0928**	0.0304	0.0984**	0.0303	0.1005**	0.0313
Social	0.0300	0.0256	0.0375**	0.0175	0.0281*	0.0181	0.0390**	0.0194
Economic	0.1215**	0.0501	0.1152***	0.0318	0.0922**	0.0319	0.1011**	0.0334
Health	0.1485**	0.0629	0.1287**	0.0442	0.1106**	0.0447	0.1205**	0.0462
Privacy concerns								
Privacy	0.0487**	0.0217	0.0479**	0.0150	0.0405**	0.0153	0.0494**	0.0162
Location and dwelling								
Location	0.1255*	0.0454	0.0269	0.0300	0.0744*	0.0312	0.0474	0.0410
Dwelling	-0.1752**	0.0532	-0.0683*	0.0355	-0.1163**	0.0375	-0.1032**	0.0424
Socio-demographic								
Age	-0.0008	0.0014	-0.0033*	0.0010	-0.0012	0.0010	-0.0025	0.0016
Gender	-0.0184	0.0441	0.0061	0.0296	-0.0082	0.0300	-0.0054	0.0317
Education	-0.0051	0.0083	0.0043	0.0055	-0.0031	0.0062	-0.0001	0.0060
Energy curtailment								
Unplug	0.0327**	0.0192	0.0267**	0.0134	0.0258**	0.0133	0.0292**	0.0139
Heating	-0.0024	0.0194	0.0285**	0.0137	0.0022	0.0140	0.0145	0.0150
Energy efficiency								
LED	0.0568**	0.0245	0.0445**	0.0154	0.0397**	0.0166	0.0435**	0.0172
ρ							0.5013*	0.2743
AIC	2525.379		1976.634		1935.329		1934.683	
N. observations	1001		1001		1001		1001	

Note: Levels of significance: **p<0.10*, ***p<0.05*, and ****p<0.01*. Robust standard errors in parenthesis.

appear to affect the frequency of app utilisation and adoption in diverse ways. Most importantly, with regard to the social dimension, the latter shows the forces of the neighbourhood for testing and experimenting new devices; in this regard, individuals holding a higher degree of environmental sensitivity may likely to be pushed by their relatives to adopt eco-friendly solutions[10]. However, when the energy app is frequently used, social pressure is not key anymore, and explaining factors become more related to environmental and health concerns, without excluding costs issues. This last finding is also in line with Bhati et al. (2017)[11], for which cutting electricity costs is of primary importance in energy saving. Surprisingly, however, these factors do not influence the adoption stage. More generally, our results show that the extrinsic form of motivation (and especially social pressure) is significant in stage 1 (app installation). Conversely, in stage 2 (frequency of use), both sources of motivation are important, but social pressure no longer plays a unique role.

Energy behaviours in the green context

As reported above, results from Tab. 3 denote a significant positive level of correlation between the environmental component and energy behaviours, with the exception of the heating variable; the latter seems conversely more correlated to the economic/financial component. When considering the variables associated to energy curtailment and energy efficiency behaviours, although mixed results emerge between adoption and use stage, we observe a stronger alignment for the same results towards the use stage, as it is the case for economic and environmental concerns. Specifically, with reference to curtailment behaviour, it appears that individuals who are accustomed to turning off the heating when leaving the apartment, seem to have on average a higher probability of installing energy tracking apps, rather than increasing the frequency of utilisation. Conversely, individuals who are more used to unplugging unutilized electronic devices seem to be the ones using the energy app on a more regular basis. In a similar fashion, in relation to efficiency behaviour, it emerges that individuals who are keener to install energy-saving LED devices are also more likely to have a higher degree of frequency of app usage. All in all, these results suggest that, in a first stage, the adoption of energy apps is driven by cost savings exclusively, with individuals paying attention to the management of the heating system and similar types of curtailment behaviours. However, in a second stage, other issues (such as environmental issues) are considered by citizens, who might want to learn more about unplugging and eco efficient appliances such as LED, possibly using regularly the energy app in this attempt. A possible interpretation is that in

[10] Lazaric et al. (2019)[39] show that what is called "green neighbourhood" matters, since this produces local positive externalities promoting new behaviours.

a first stage, some information has to be collected and some practices learnt, opening the room in a second stage to new issues such as unplugging devices and LED appliances.

Privacy concerns

Next, interesting results emerge when considering the degree of concern related to privacy issues. Indeed, contrary to what recent works in the smart home technologies literature could infer, privacy concerns have no significant impact on adoption.

Our results are in line with Lorenzen-Huber et al. (2011), who found that some individuals are able to embrace the benefits of the technology without being bothered by privacy issues. However, as highlighted for other services such as biometric services (Lancelot-Miltgen et al., 2013[38]), social network services (Cecere et al., 2015[18]) or smart meters (Gerpott and Paukert, 2013[24]), individuals who are more concerned about privacy issues are at the same time more likely to have a higher frequency of utilisation of energy tracking apps. This result could contribute to explain the conflicting findings observed in the literature on smart home technologies; in this regard, the role of privacy concerns could be less important in the stage of adoption of a smart home technology, while playing a more significant role in the utilisation stage. In this context, our finding can be related to the so called "privacy paradox" introduced by Acquisti (2004)[1], explaining how individuals with high levels of concern over privacy tend to expose and disclose their personal data more readily than others. As also explained by Wilson et al. (2017)[69], at a prospective and early stage of adoption, privacy concerns associated to smart home technologies are not prevalent, nor salient. However, such concerns become more prevalent at a more advanced stage. In other words, privacy concerns are not determinant for adoption (since app installation does not require the disclosing of personal data), but data privacy becomes more of a concern when using the app.

Socio-demographic characteristics, location and dwelling

With reference to socio-demographic variables, when considering the age variable, the ordered probit model suggests that older individuals tend to be less likely to make use of energy tracking apps. This result appears rather straightforward and in line with the literature. As suggested by Michaels and Parag (2016)[41], such a finding may likely relate to a higher degree of familiarity with technology by younger individuals, since the latter more commonly utilize technology in their day-to-day life compared to the elderly. Nonetheless, an additional interesting finding from our analysis emerges when considering the coefficient estimates deriving from the hurdle and zero-inflated models. Indeed, these two estimators indicate that the negative effect exerted by the age variable affects the choice of app installation, rather than the frequency of utilisation. Then, the gender variable does not seem to affect the probability of app installation, nor the frequency of utilisation. The same finding emerges when considering the average years of education of individuals. If compared to the contrasting and inconclusive findings detected in the smart home technology adoption literature (Karlin et al., 2015[34]; Parag and Butbul, 2018[49]; Baudier et al., 2019[9]), the effects exerted by gender and education still remain unclear, thus calling for the need of further research investigation in this domain.

With reference to location, surprisingly, it seems that on average, individuals residing in Nice are less likely to install energy tracking apps with respect to individuals in Bordeaux. Indeed, in consideration of the smart energy solutions and actions implemented in the city of Nice aimed at optimizing domestic energy behaviour, one might have expected the opposite result. On the other hand, it might be argued that individuals who already have (or are exposed to) a high degree of environmental/energy sensitivity, may also be less likely to rely upon devices measuring energy consumption; this trend of natural adopters not actually adopting a technology has indeed been registered in a recent contribution in *Science* (Catalini and Tucker, 2017[17]). In this regard, our explanation relies in the fact that when an individual lives in a smart city environment and is often exposed to achieve better behavioural outcomes in terms of energy efficiency, he/she may find energy tracking devices redundant. In fact, the implementation and diffusion of all the smart solutions targeting domestic energy optimization (such as the empowerment of smart grids and storage energy devices), may have already represented, for most residents in Nice, a sufficient element of energy optimization, thus limiting the usage of energy tracking apps. On the other hand, individuals that are more distant with an energy-efficient environment at their own city level, may find user-friendly and easy to use devices generated for households of more immediate value compared to their smart cities counterparts; in such a perspective, this can play a role of enhanced access or short cut access to energy sustainable behaviours.

Then, in relation to dwelling type, being an owner, rather than a tenant, significantly decreases the frequency of energy app usage. According to Franke and Nadler (2019)[21], this result may be explained by the fact that on average, in the European Union, owners generally possess a better awareness of the energetic performance of their house, and therefore are less prone to rely upon an extensive usage of apps to track energy consumption. As highlighted in Sweeney et al. (2013)[57] and Wilhite et al. (1996)[68], different housing characteristics in the two cities such as house size and housing equipment (but also differences in weather and temperature) may as well exert a role.

Finally, a positive and significant value for the rho coefficient emerges, thus suggesting the presence of a positive correlation between the unobservable components of the two latent equations capturing the two different decision choices made by the individuals on energy tracking apps.

5 Conclusion and policy implications

This paper investigated the determinants of energy tracking app usage by individuals residing in the two French cities of Nice and Bordeaux. Specifically, utilizing survey-level data, we contributed to shed more light on the different drivers affecting the adoption and the frequency of utilisation of digital solutions related to the domestic tracking of energy consumption. Although in the theoretical literature some contributions have already analysed the drivers pushing individuals to make use of smart home technologies, very few studies have hitherto investigated the specific case of smart energy tracking apps. For our analysis, besides providing new empirical results, we built an original framework inspired by the strands of literature on smart cites and smart home technology adoption, which in turn is able to nurture with the incorporation of additional specificities. Specifically, in our framework, the impact exerted by the drivers related to perceived benefits of smart energy technology usage, privacy issues, location and dwelling type, energy behaviours in the green context, and socio-demographic characteristics, are explored. In order to distinguish between adoption and frequency of utilisation of smart energy apps, we adopted a Zero-Inflated Ordered Probit (ZIOP) model, which also has the advantage of taking into account an excessive number of zero observations emerging from the data.

Ultimately, our empirical estimates provide interesting results and reveal how energy tracking app adoption and frequency of utilisation are driven by different factors. First, the factors related to smart city characteristics in relation to the usage of smart technologies seem to affect the decision of adoption of smart apps rather than the frequency of utilisation. On the other hand, the latter seems to be mainly affected by the individual characteristics related to the perceived benefits of using smart apps, dwelling type and privacy issues; in this regard, we additionally provide empirical validation to the emergence of the privacy paradox. With regard to socio-demographic characteristics, the latter do not seem to exert a significant impact on the adoption stage, nor on the frequency of utilisation of energy tracking apps, with the sole exception of the age variable, whose impact on energy app adoption results to be negative; this finding validates previous results detected in the literature on the adoption of smart energy technologies. With reference to energy behavioural variables in the green context, we then obtained mixed results. Specifically, our findings indicate that energy curtailment behaviours positively affect both the frequency of use and the adoption of energy tracking apps; at the same time, in relation to energy efficiency behaviours, it appears that reduced investments in efficient energy technologies (such as the installation of LED bulbs), do exert a positive significant impact on the frequency of app usage, but not on the adoption stage. Finally, from our estimates, it appears how the decision of energy tracking app adoption and frequency of utilisation, besides being driven by different observed factors, are also positively related according to unobserved components.

Contributions

Contributions of this paper to the literature are fourfold. First, this paper is among the firsts to focus on the usage of energy tracking apps, placing citizens at the centre of city development; the latter further represents a topic which has attracted limited consideration in the smart cities literature, especially in relation to smart home technology adoption, where essential characteristics of smart energy applications are usually not taken onboard. Second, this paper generates an original framework that contributes to the adoption literature, since it places a central focus on key determinants of actual adoption of a smart energy app and its frequency of use in a context of urban development.

Third, our analysis also provides an empirical contribution in comparing a smart city *versus* a non-smart city environment for the adoption and use of smart energy apps; in fact, such an issue is generally not considered in studies belonging to the smart cities literature. In this regard, a significant difference in the utilisation of energy apps depending on location might reflect the role exerted by smart energetic technological solutions in affecting citizens' energy optimization behaviour. Fourth, this paper relies upon original survey-level data, using a two-part econometric model which allows to accommodate the distinction between adoption and frequency of app usage.

5.1 Policy implications

The role of citizens is acknowledged in a series of recent studies on energy consumption and adoption of new energy services (Wustenhagen et al., 2007[72]; Aitken, 2010[4]; Strazzera et al., 2012[56]; Motosu and Maruyama, 2016[43]; Scherhaufer et al., 2017[54]; Prosperi et al., 2019[51]), identifying the different drivers and impediments observed in different national contexts. The latter generally include factors such as socio-demographic characteristics (age, gender, education) as well environmental *versus* financial concerns, or individual *versus* collective issues (Thogersen and Gronhoj, 2010[59]; Olander and Thogersen, 1995[46]). In this literature, we also find arguments identifying a number of reasons why households might not adhere to new solutions, such as the convenience of doing what one is used to do, the lack of motivation, and the whole range of impediments that make behavioural change difficult. In addition, every single individual has his/her own psychological traits with value priorities, outcomes expectations, attitudes, personal norms and self-efficiency (Vringer et al., 2007[64]). The latter need to be compared with contextual variables such as structural conditions (type of dwelling and district, technological standards, format and frequency of information), socio-demographic characteristics, household size and composition, or cultural and economic aspects (e.g., social norms and economic incentives) (Black et al., 1985[12]). In that context, Mosannenzadeh et al. (2017)[42] confirmed that inertia, lack of values and interest in energy optimisation measurements, as well as insufficient information on potential users and consumers, can lead to low acceptance of new solutions. Alternatively, the authors claim that the involvement of target groups from the early stage of development of these projects taking into account residents' needs and attitudes in advance, can remove barriers in the adoption of smart energy projects in Europe. As a matter of fact, disparities in users' adoption and frequency of utilisation of smart apps can contribute to foster or hamper smart city strategies in European cities; therefore, the success of such strategies depends on the creation of new technological solutions to be accepted and adopted by citizens.

Our study bear policy implications in this line, calling for the importance of reducing uncertainties perceived by lead users of smart energy apps, and more generally by lead users of smart home technologies. Above all, our findings confirmed first of all an important inconsistency concerning the role of individuals' privacy concerns on adoption and use of smart energy apps. Notably, the empirical results of our analysis suggest that privacy issues matter when using smart home technologies. In this regard, policymakers might play an important role in mitigating such perceived risks by guaranteeing that smart app providers will respect laws and guidelines on data and privacy protection during the app conception and implementation phases. Policy makers could also better inform people about the related real risks, in terms of privacy, of smart home technologies. For example, they could carry out an awareness campaign on why and why not there can be dangers in terms of privacy violation when using smart energy apps. In addition, reluctant people could benefit from training initiatives in the use of apps. By doing so, policymakers would help those people to learn more about how to use smart apps without running the risk of privacy violation. Finally, in case people were not sufficiently aware by how the General Data Protection Regulation (GDPR) is applied and respected by suppliers of smart home technologies, an information campaign could be carried out on this subject, with a specific focus on smart energy apps. More generally, policy makers could conduct a training campaign on what the GDPR is, and how it works (incidentally, whether the recent GDPR regulation is sufficient in reassuring smart technology users, is still a pending question). On the other hand, these policy implications shall be consolidated with an in-depth examination of energy challenges in smart *versus* non-smart cities. Indeed, our analysis has demonstrated how the diffusion of energy tracking apps in a location already reputed as smart, can be of less relative value compared to another location which is not yet listed as a smart city. Particularly, for citizens living in a smart city environment, these devices might in the end generate additional costs or efforts compared to their usual trend of behaviour which is already oriented towards energy sustainability. In sum, the benefit to be expected is lowered due to redundancy. As a counterpart, citizens that are not embedded in a smart city location may find a valuable advantage in the use of smart energy tracking apps; indeed, the latter can provide to them a reliable feedback tool to cope with the energy invisibility problem. Nonetheless, a more in-depth investigation of these aspects is beyond the current contribution, and may also be seen as a limit of this work to be overcome in future research.

Appendix

Table A1: Probability of app installation (marginal effects, ZIOP(C)).

	ZIOP						ZIOPC					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Benefit-related												
Environment	0.0010	0.0012	0.0104	0.0144	0.0079	0.0094	0.0010	0.0022	0.0104	0.0124	0.0059	0.0079
Social	0.0012	0.0107*	0.0166*	0.0127**	0.0159*	0.0195**	0.0104	0.0119	0.0166*	0.0119**	0.0147*	0.0189*
Economic	0.0000	0.0001	0.0438*	0.0412*	0.0284	0.0354*	0.0000	0.0001	0.0442*	0.0385	0.0254	0.0331
Health	-0.0002	0.0006	0.0095	0.0216	0.0180	0.0202	-0.0001	-0.0004	0.0097	0.0190	0.0153	0.0182
Privacy concerns												
Privacy		0.0102	0.0124	0.0188*	0.0132	0.0173		0.0012	0.0203	0.0177	0.0121	0.0163
Location and dwelling												
Location			-0.0311***	-0.0331***	-0.0364**	-0.0447**			-0.0316***	-0.0328***	-0.0351***	-0.0345**
Dwelling			-0.0123	0.0205	0.0119	0.0177			0.0116	0.0212	0.0128	0.0182
Socio-demographic												
Age				-0.0024***	-0.0018**	-0.0022**				-0.0023*	-0.0017**	-0.0021**
Gender				-0.0006	-0.0010	-0.0009				-0.0044	-0.0015	-0.0026
Education				0.0055	0.0035*	0.0046				0.0055	0.0036*	0.0045
Energy curtailment												
Unplug					0.0048						0.0052	
Heating					0.0144**						0.0139**	
Energy efficiency												
LED						0.0103						0.0097
ρ							0.2815	0.3687	0.4122	0.4747	0.4859*	0.4591*
AIC	2018.05	2006.937	1980.743	1947.656	1937.495	1943.118	2016.253	2005.377	1978.768	1946.061	1936.878	1941.465
Log-likelihood	-997.0249	-989.4685	-972.3715	-949.8278	-940.7473	-945.5590	-997.1263	-989.6884	-972.3839	-950.0304	-941.4392	-945.7325
N. observations	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

Note: Levels of significance: *$p<0.10$, **$p<0.05$, and ***$p<0.01$.

Table A2: Frequency of app usage (marginal effects, ZIOP(C)).

	ZIOP						ZIOPC					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Benefit-related												
Environment	0.1213***	0.1135***	0.1177***	0.1139***	0.1033***	0.1079***	0.1215***	0.1125***	0.1173***	0.1161***	0.1055***	0.1098***
Social	0.0221	0.0313	0.0245*	0.0300*	0.0277*	0.0299*	0.0275	0.0265	0.0222*	0.0369**	0.0381**	0.0365*
Economic	0.1323***	0.1213***	0.0924**	0.0894**	0.0904**	0.0908**	0.1209***	0.1206***	0.0869**	0.1004***	0.1074***	0.1013***
Health	0.1050***	0.1319***	0.1053**	0.1020**	0.1032**	0.1102**	0.1280**	0.1251**	0.1048**	0.1060**	0.1117**	0.1149**
Privacy concerns												
Privacy		0.0501**	0.0443**	0.0437**	0.0380**	0.0460**		0.0505***	0.0415**	0.0491***	0.0462***	0.0514***
Location and dwelling												
Location			0.0566	0.0569	0.0676*	0.0659*			0.0659	0.0382	0.0401	0.0497
Dwelling			-0.1239***	-0.1133***	-0.1131***	-0.1176***			-0.1229**	-0.1040**	-0.0992**	-0.1100**
Socio-demographic												
Age				-0.0008	-0.0007	-0.0013				-0.0016	-0.0020	-0.0020
Gender				-0.0194	-0.0111	-0.0152				-0.0189	-0.0092	-0.0145
Education				-0.0015	-0.0023	-0.0026				0.0005	0.0008	-0.0009
Energy curtailment												
Unplug					0.0279**						0.0312**	
Heating					0.0040						0.0160	
Energy efficiency												
LED						0.0426**						0.0455**
ρ							0.2815	0.3687	0.4122	0.4747	0.4859*	0.4591*
AIC	2018.05	2006.937	1980.743	1947.656	1937.495	1943.118	2016.253	2005.377	1978.768	1946.061	1936.878	1941.465
Log-likelihood	-997.0249	-989.4685	-972.3715	-949.8278	-940.7473	-945.5590	-997.1263	-989.6884	-972.3839	-950.0304	-941.4392	-945.7325
N. observations	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001	1001

Note: Levels of significance: *$p<0.10$, **$p<0.05$, and ***$p<0.01$.

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