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The heat is off! The role of technology attributes and individual attitudes in the diffusion of Smart thermostats – findings from a multi-country survey

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ABSTRACT

Smart thermostats may provide up to 10% savings in residential thermal energy use without loss of comfort, yet their diffusion has typically been slow. To better understand adoption of these devices, we conducted an online survey with approximately 5,500 respondents from eight European countries that included both a discrete choice experiment (DCE) and stated past adoption of smart thermostats. The results we obtained by estimating mixed logit models suggest that households value heating cost savings, remote temperature control, the display of changes in energy consumption, and recommendations by experts, albeit with substantial heterogeneity across countries; in comparison, subsidies are positively valued in all countries except for Germany and Spain, and recommendations by energy providers in all countries except Poland where they are negatively valued. Further, the findings provide evidence that consumer innovativeness reinforces the acceptance of technical attributes (heating cost savings, feedback functionalities, and remote temperature control), that privacy concerns reduce the acceptance of remote functionalities, and that stronger environmental identity reinforces the acceptance of environmentally related attributes (heating cost savings and feedback functionalities). The results we obtained from estimating binary response models of stated past adoption of smart thermostats are generally consistent with those of the DCE.

1. Introduction

Smart devices, characterized by their ability to detect changes in human behavior and environmental stimuli and to react to these changes through technology (Chan et al., 2008; Orwat et al., 2008), are being developed rapidly in a variety of areas. In private households, the development of smart technologies is particularly visible in smart home devices, such as smart health monitoring devices (Liu et al., 2016), smart security systems (Kumar et al., 2019), and smart appliances (D'hulst et al., 2015). Among these smart devices, smart heating control devices (hereafter called smart thermostats) are especially valued for their environmentally beneficial potential (Lu et al., 2010). These devices employ sensors and artificial intelligence to provide users with automatized heating control and feedback about energy consumption and to enable users to implement more efficient heating schedules (for instance, avoiding unnecessarily high temperatures at night or when a dwelling is empty). Further, some of those devices enable users to adjust temperatures remotely, for example through a smart phone application. With these capacities, smart thermostats have the potential to reduce energy consumption, cut household heating bills, and lower carbon emissions. Previous research has shown that smart thermostats can save users as much as 10% in thermal energy consumption without loss of comfort (Kleiminger et al., 2014; Liang et al., 2012). Insofar as space heating accounts for a large fraction of residential energy use (for instance, 52% in the European Union (EU) (European Commission, 2017)), smart thermostats may contribute substantially to achieving energy efficiency and hitting climate policy targets. Therefore, studying factors that lead to the acceptance of smart thermostats is particularly relevant today because these devices are part of the rapidly developing market for smart home devices and because of their potential environmental impact.

In this paper, we empirically analyze household acceptance of smart

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thermostats through a large-scale survey that employs a discrete choice experiment (DCE) to estimate individuals' willingness-to-pay (WTP) for various smart thermostat attributes as well as self-reported adoption of these devices.[1] Our study contributes to the literature in several ways. First, it focusses on smart thermostats, a relatively new technology (Greenough, 2016) that has great potential for reducing energy consumption but on which few empirical studies have been conducted. Second, in contrast to previous studies on smart thermostats, we use the DCE approach to estimate the trade-offs between several key smart thermostat attributes and to calculate individuals' WTP for these attributes. Third, our analysis of our DCE with smart thermostats accounts for preference heterogeneity through the explicit integration of individual attitudes such as consumer innovativeness, privacy concerns, and environmental identity, which have been shown in previous research to be related to smart device adoption or to the adoption of energy-efficient technologies. Finally, to corroborate and complement the DCE findings, we compare the results with those derived by estimating binary response models with which we analyze factors related to stated past adoption of smart thermostats. This two-pronged analysis enables us to provide some answers related to the attitude–behavior gap. Finally, in contrast to previous studies that were typically conducted in single countries, we use a large-sample survey with demographically representative samples selected in eight European countries (France, Germany, Italy, Poland, Romania, Spain, Sweden, and the United Kingdom (UK)) that represent a wide range of political, geographical and socioeconomic contexts and together account for about 80% of the EU's population and energy use (European Commission, 2018). This facilitates cross-country comparisons but also yields generalizable predictions for specific socio-demographic groups.

The remainder of this paper is organized as follows: In Section 2 we review the literature on smart home device adoption and on the attitude–behavior gap for the adoption of environmentally friendly products and develop hypotheses related to smart thermostat adoption. In Section 3 we describe the methodology, including the econometric models, the survey, and the variables used. In Section 4 we present and discuss the results. In the final Section 5 we summarize the main findings and derive implications for policy-makers and companies.

2. Literature review and hypothesis development

In this section, we first review the literature on smart home technologies and especially smart home energy devices to identify the most relevant smart thermostat attributes and their impact on smart thermostat adoption. In a second step, we review the appropriate literature on individual attitudes affecting the acceptance of smart home technologies and of energy-efficient technologies to develop hypotheses related to the impact of selected attitudes on smart thermostat adoption.

2.1. Smart thermostat attributes

Smart thermostats have become available in the growing market for smart home technologies designed to facilitate energy management (hereafter smart home energy devices). Ford et al. (2017) categorize these technologies into user interfaces (e.g. energy portals, home displays, load monitors), smart hardware (e.g. smart appliances, smart lighting systems, smart thermostats), and platforms (e.g. web service platforms).

Studies on smart home hardware help identify the most relevant attributes for the adoption of these devices. The first set of attributes consists of the financial costs and benefits associated with the devices. Not surprisingly, previous research shows that upfront costs matter and that consumers are reluctant to purchase such devices when prices rise (e.g. Daim and Iskin, 2010). Shin et al. (2018) for instance show that South Korean consumers intend to purchase cheaper home devices sooner than more expensive devices. Further, financial incentives such as rebates and subsidized loans have frequently been offered by governments to promote the adoption of energy-efficient technologies to help achieve energy and climate policy targets, or by utilities in demand-side management programs. Previous studies typically find that such financial incentives encourage the adoption of new heating systems and energy-efficient home appliances (Achtnicht, 2011; Achtnicht and Madlener, 2014; Alberini and Bigano, 2015; Datta and Gulati, 2014; Olsthoorn et al., 2017). Smart features of smart thermostats provide additional benefits, but they may also involve higher levels of complexity and perceived technological and financial risks (Ehrenhard et al., 2014; Rijsdijk and Hultink, 2009; Wilson et al., 2017). Therefore, subsidies may be needed to overcome these additional barriers. In sum, we propose:

H1a: Price is negatively associated with smart thermostat adoption.

H1b: A higher subsidy is positively associated with smart thermostat adoption.

Smart home energy devices have been designed to help consumers manage their energy consumption. In a study focusing on the functionalities of smart home energy devices, Ford et al. (2017) identify energy cost savings as one of the key features of these devices that dominate consumer decision-making. Indeed, the potential of smart home energy devices to reduce energy costs appears to be one of the main motivations to adopt such devices (e.g. Daim and Iskin (2010) for smart thermostats in the USA; Pepermans (2014) for smart meters in Belgium; Wilson et al. (2017) for a wide range of smart home technologies including smart home energy devices in the UK). In general, higher energy cost savings have typically been found to increase household propensity to adopt energy-efficiency technologies such as new heating systems (e.g. Achtnicht, 2011; Achtnicht and Madlener, 2014) and energy efficient appliances (e.g. Li et al., 2016; Newell and Siikamäki, 2014). Because smart thermostats affect only heating costs, we propose:

H2: Heating cost savings enabled by the device are positively associated with smart thermostat adoption.

Examining the effects of feedback on energy consumption, studies comprising a vast literature in the area of electricity consumption (focusing mostly on the introduction of smart meters) consistently find that electricity consumption feedback helps reduce electricity demand (e.g. Darby, 2006; Schleich et al., 2017). Ford et al. (2017) identify the provision of feedback to users about energy consumption as one of the most prevalent features of smart thermostats. Similarly, studies focusing on smart home energy devices show that consumers particularly value energy consumption feedback (e.g. Kaufmann et al., 2013 for the choice of smart meters in Switzerland). We therefore propose:

H3: The availability of energy consumption feedback is positively associated with smart thermostat adoption.

Smart home technologies are characterized by the possibility of controlling the devices remotely through smart phone applications, and this remote control capability is one of the key features of smart thermostats (Ford et al., 2017). Consumers have been found to appreciate the convenience of these remote control functionalities for smart meters (e.g. Kaufmann et al., 2013). Hong et al. (2016) also find that US car drivers value remote control functionalities for smart car keys even though they value such functionalities less for car–home connectivity. Overall, we propose:

H4: The availability of remote control functionalities is positively associated with smart thermostat adoption.

[1] The marketing literature, in particular, refers to a DCE as 'choice-based-conjoint analysis' to distinguish this method from other types of conjoint analyses. We follow Carson and Louviere (2011), who suggest using 'discrete choice experiment' to promote common terminology.

We have so far focused on the financial and technical characteristics of smart thermostats. Previous literature has found that complexity as well as technological and financial risks impede the acceptance and adoption of smart home devices (Ehrenhard et al., 2014; Rijsdijk and Hultink, 2009; Wilson et al., 2017). In such situations, consumers rely on product recommendations to reduce the difficulty associated with choosing among multiple alternatives (Duhan et al., 1997; Senecal and Nantel, 2004). According to Andreasen (1968), the sources of information to which consumers may turn for product recommendations can be classified based on their personal ties to the consumer and on their degree of independence from the products sold. Friends, family, and colleagues are generally considered to have strong ties to consumers and to be quite neutral in their recommendations; such sources of information are particularly relevant when consumers are searching for affective support for their purchase decisions (Duhan et al., 1997). In contrast, consumers searching for expertise tend to turn to independent experts, who are characterized by their weak ties to consumers and their neutrality towards the products or services sold (Duhan et al., 1997). For smart energy devices, such experts can for instance be publicly sponsored consultation offices focusing on energy efficiency that are typically available in many EU countries (Achtnicht, 2011), or web-based expert sites such as www.ademe.fr in France and www.energysavingtrust.org.uk in the UK. Previous studies have found that households have a greater WTP for energy-efficient retrofits recommended by independent energy advisers (Achtnicht, 2011; Achtnicht and Madlener, 2014). Finally, products may also be recommended by the companies selling them or selling related services, a mode of recommendation characterized by stronger (more personal) ties to consumers, but a lack of independence. While one might expect consumers to be skeptical of such potentially biased advice (Andreasen, 1968), consumers often turn actively to salespeople for advice; in fact, utility providers are taking on a new role as "trusted advisors" (Honebein et al., 2012). To sum up, we expect to find differences in consumer preferences for product recommendations stemming from friends and family, independent energy experts, and energy providers. Given the technical nature of the products, we expect that expertise will play a greater role than emotional support and therefore propose:

H5: Recommendations through experts (either energy experts or energy providers) are more positively associated with smart thermostat adoption than recommendations through friends and family.

2.2. Individual attitudes

Previous research has identified some key attitudes that can affect consumer acceptance of smart thermostats. Existing empirical studies have found consumer innovativeness to be positively related to the adoption of new technologies such as computer software (Foxall and Bhate, 1999), new audio and video appliances (Hirunyawipada and Paswan, 2006), e-commerce purchasing systems (Jackson et al., 2013), and remote mobile payments (Liébana-Cabanillas et al., 2018; Slade et al., 2015).[2] Marikyan et al. (2019) also stresses the importance of consumer innovativeness for the adoption of smart home devices. Thus, the adoption of smart thermostats is expected to depend on consumers' attitudes towards new products in general such as psychological resistance to using innovative technology. So far, very few studies have empirically explored the relationship between consumer innovativeness and adoption of smart home appliances. In a study for highly educated business and engineering students in France ("digital natives"), Baudier et al. (2020) did not find a statistically significant effect of personal innovativeness on intended use of smart home technologies—possibly because there was little variation in personal innovativeness in their sample. Based on the literature, we expect that consumer innovativeness will affect acceptance of smart thermostats, and especially acceptance of the technical features of these thermostats: heating cost savings (since those are obtained through the use of the technology and not through changes in behavior or in heating systems), the availability of feedback (typically provided through some displays) as well as the availability of remote control functionalities. We therefore propose:

H6a: Consumer innovativeness is positively associated with smart thermostat adoption.

H6b: Consumer innovativeness moderates the association between technical attributes (heating cost savings, availability of feedback and of remote control functionalities) and smart thermostat adoption, such that when consumer innovativeness increases, the association between technical attributes and smart thermostat adoption is reinforced.

For many potential customers, the benefits of smart home technologies remain opaque and concerns may remain about privacy. Privacy concerns have been found in the literature studying consumer acceptance of smart home devices (e.g. Balta-Ozkan et al., 2013) and smart meters (e.g. Hoenkamp et al., 2011; Krishnamurti et al., 2012; Pepermans, 2014), and more recently also consumer acceptance of smart glasses (Rauschnabel et al., 2018). In the daily use of smart products, privacy concerns occur when consumers use online services and third parties may obtain access to their personal information. Privacy concerns therefore not only are likely to discourage the adoption of smart thermostats but are also expected to reduce the acceptability of product functionalities that require an internet connection and data transfer, such as remote control via smartphones.

H7a: Privacy concerns are negatively associated with smart thermostat adoption.

H7b: Privacy concerns moderate the association between the availability of remote control functionalities and smart thermostat adoption, such that when privacy concerns increase, the association between the availability of remote control functionalities and smart thermostat adoption is reduced.

Consumers have also been found to fear a loss of control and autonomy when using smart products, because they feel that using these products reduces their freedom to choose or act on their own (e.g. Rijsdijk and Hultink, 2003; Schweitzer and Van den Hende, 2016) or increases their dependence on technology and electricity networks (Wilson et al., 2017). Autonomy concerns are therefore likely to lower the acceptability of smart thermostats and we therefore propose:

H8: Concerns about loss of autonomy are negatively associated with smart thermostat adoption.

Finally, because using smart thermostats potentially lowers energy consumption and emissions, pro-environmental attitudes may also affect adoption of these devices. While Balta-Okzan et al. (2013) conclude that environmental motivations are not among the key drivers of smart home technology adoption in general, Marikyan et al. (2019) stress the importance of environmental benefits for the acceptance of smart home energy devices. Further, previous empirical research typically finds energy-efficient technology adoption to be positively related to pro-environmental attitudes (e.g. Mills and Schleich, 2012; Ramos et al., 2015; Schleich et al., 2019). The effects of pro-environmental attitudes should be particularly strong for the attributes that are directly linked to energy consumption, that is, heating cost savings and energy consumption feedback. We therefore expect:

H9a: Environmental attitudes are positively associated with smart thermostat adoption.

H9b: Environmental attitudes moderate the association between environmentally related attributes (heating cost savings and availability of energy consumption feedback) and smart thermostat adoption, such that when environmental attitudes grow stronger, the association

[2] Rogers (2002) defines innovativeness as "the degree to which an individual or other unit of adoption is relatively earlier in adopting new ideas than other members of a social system".

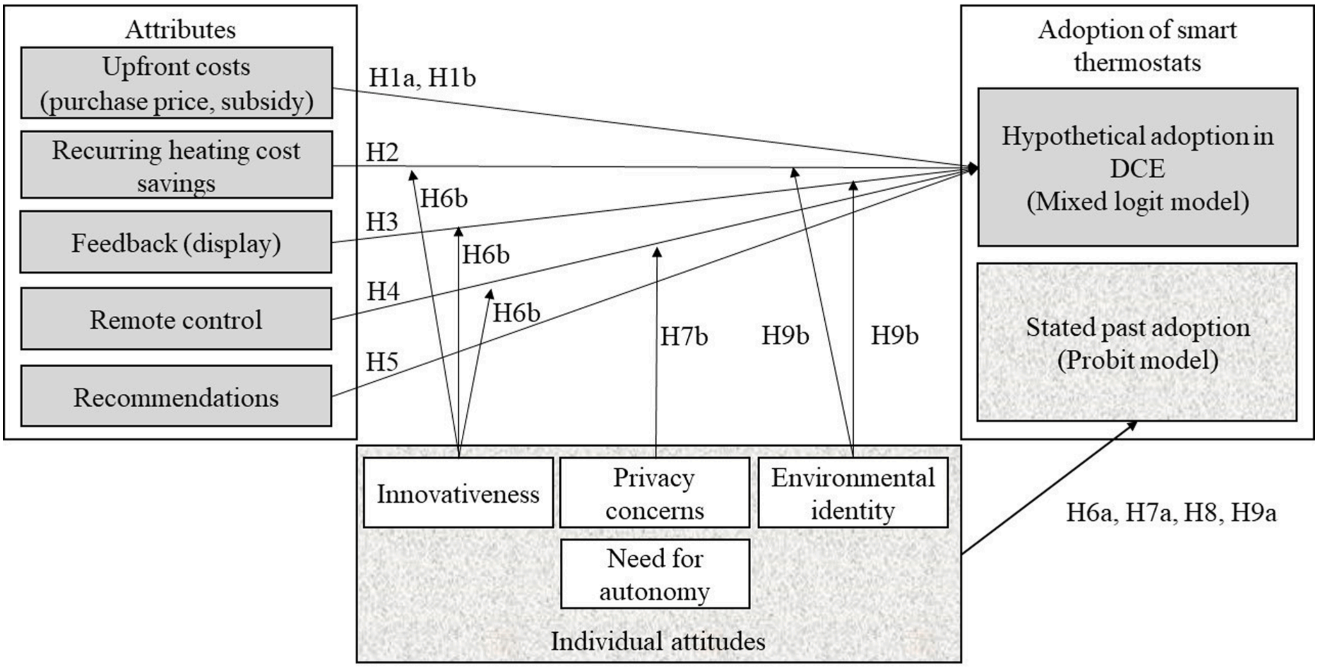


Fig. 1. Research framework.

between environmentally related attributes and smart thermostat adoption is reinforced.

2.3. Research framework

Fig. 1 summarizes the framework to be tested empirically in the following sections. Following our review of the literature, this framework distinguishes between two main types of factors affecting the adoption of smart thermostats: device attributes (purchase price, whether a device is eligible for a subsidy, heating cost savings, feedback and remote control functionalities, and sources of recommendations) and individual attitudes (consumer innovativeness, privacy and autonomy concerns, and pro-environmental attitudes). Further, to account for the extensive literature on attitude-gap behavior for the acceptance of environmentally friendly products (e.g. Vermeir and Verbeke, 2006), the framework distinguishes between two kinds of smart thermostat adoption: hypothetical adoption and stated past adoption. In the following sections, we present two empirical tests of this framework. The first set of analyses—based on the DCE and using mixed logit models—tests the hypotheses pertaining to smart thermostat attributes and the moderating effects of individual attitudes on the effects of these attributes on hypothetical smart thermostat adoption. The second set of analyses employs Probit models to test the effects of individual attitudes on stated past adoption.

3. Methods

We first present the design of the core empirical analysis employed in this paper: the DCE with smart thermostats. We then present the econometric models used to analyze the DCE and past adoption of smart thermostats. In the final subsection we describe the multi-country survey.

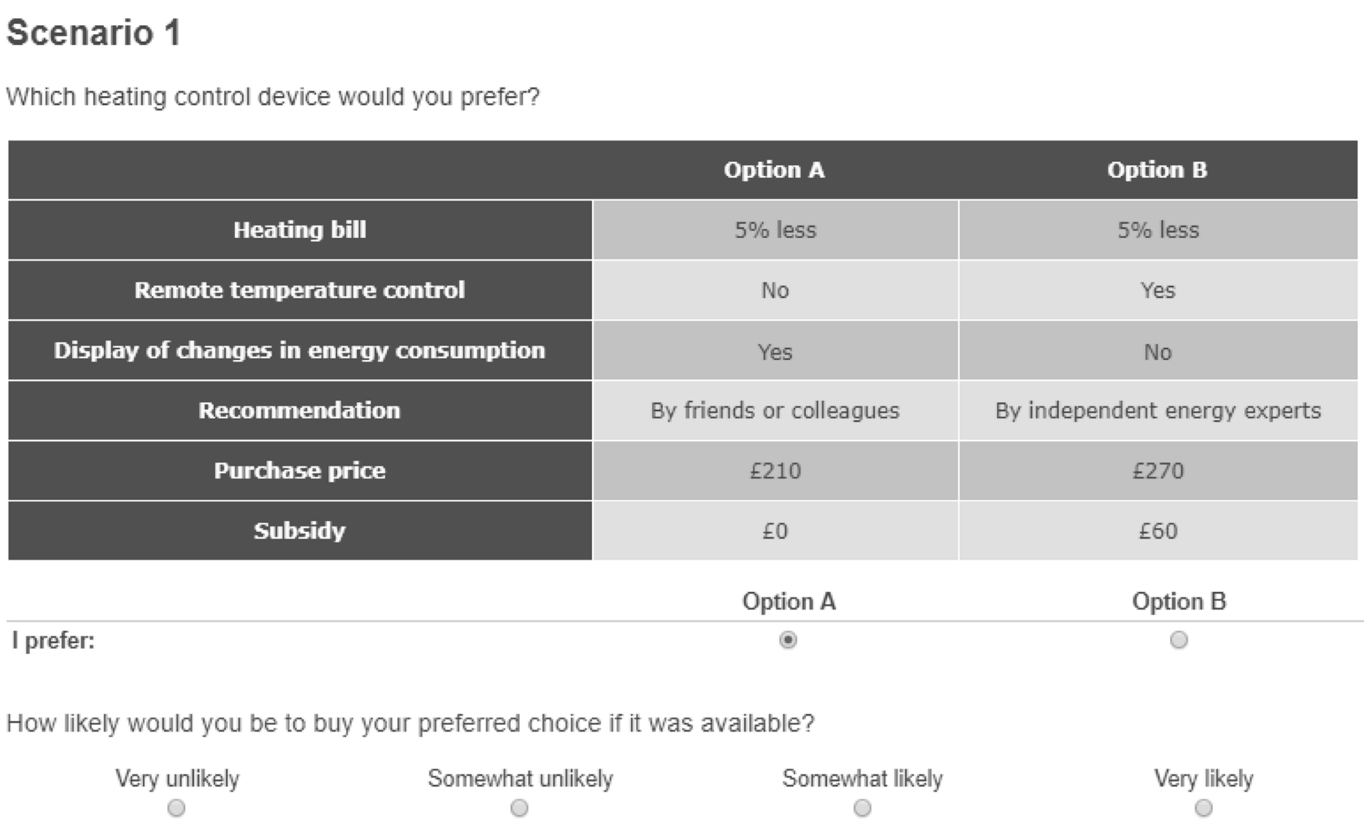
Table 1
Attributes and levels considered in the smart thermostat choice experiment.

Attribute	Levels	Variable name
Heating bill	1% less, 5% less, 10% less	*savings*
Remote temperature control	Yes, No	*remote*
Display of changes in energy consumption	Yes, No	*display*
Recommendation	by friends or colleagues	reference level
	by independent energy experts	*rec_expert*
	by your energy provider	*rec_provider*
Purchase price	€150, €180, €210, €240, €270, €300	*price*
Subsidy	€0, €20, €40, €60	*subsidy*

3.1. Design of the discrete choice experiment

Conceptually, a DCE relies on the Lancasterian theory of demand (Lancaster, 1966) and the random utility framework (McFadden, 1974). It involves the generation and analysis of choice data through the construction of a hypothetical market using a survey in which respondents are asked successively to choose one alternative from a given choice of product alternatives characterized by a set of attributes with various combinations of attribute levels. A DCE is generally considered an appropriate multi-attribute method for the estimation of preferences for products where market data are lacking or limited (Louviere, 1992). For example, in the domain of smart energy devices, DCEs have been applied in analyzing preferences for smart meters (Kaufmann et al., 2013; Pepermans, 2014).

In our choice experiment, respondents were asked to make a series of choices between smart thermostat purchase alternatives ("*We would like to know which heating control device you would prefer, if you were making a purchase and these were your only options.*"). Guided by our review of the



Scenario 1

Which heating control device would you prefer?

	Option A	Option B
Heating bill	5% less	5% less
Remote temperature control	No	Yes
Display of changes in energy consumption	Yes	No
Recommendation	By friends or colleagues	By independent energy experts
Purchase price	£210	£270
Subsidy	£0	£60

	Option A	Option B
I prefer:	◉	○

How likely would you be to buy your preferred choice if it was available?

Very unlikely ○ Somewhat unlikely ○ Somewhat likely ○ Very likely ○

Fig. 2. Example of scenario as shown to respondents in the DCE in the UK.

literature, these alternatives were characterized by the following six attributes representing information that is relevant to customers choosing a thermostat (presented here in the order in which they were presented to the respondents): the purchase price (H1a), the capacity to reduce respondents' heating costs (H2), control of room temperature via a remote device (H4), display of changes in energy consumption (H3), a subsidy (H1b), and recommendation sources (H5). Table 1 summarizes the attributes and levels.[3] All attributes were chosen to be independent of one another. Moreover, attributes and levels were chosen to be realistic and provide options similar to smart thermostats that are available on the market. The levels chosen for each attribute were discussed and validated with heating technology experts from Fraunhofer Institute of Systems and Innovation Research (ISI) and the Technical University of Vienna who were part of the H2020 project consortium. The levels chosen for the purchase price, which is a one-time payment, correspond to the range of prices observed on the market. To calculate the subsidy amounts, we used the ratios of subsidy to purchase price that Alberini and Bigano (2015) and Olsthoorn et al. (2017) used in their experiments on new residential heating systems. The thermostats in the hypothetical choice experiment allowed respondents to reduce their heating costs by 1%, 5%, or 10%. The levels associated with this attribute were chosen based on results of studies that suggest that smart thermostats can save approximately 6% to 10% of heating energy without loss of comfort (Kleiminger et al., 2014; Liang et al., 2012). We operationalized feedback on energy consumption as the availability of a display indicating changes in energy consumption based on temperature changes, and remote control functionalities as the availability of remote temperature control. Finally, following the literature, we operationalized three types of sources of recommendation: friends and family, energy experts, and energy providers (we did not allow for joint recommendations).

To reduce the large number of possible treatment combinations and increase the efficiency of the DCE, we applied a Bayesian efficient design (Sándor and Wedel, 2001) using Ngene software (ChoiceMetrics, 2014). The priors used for the design were obtained from a pilot study with 50 UK respondents from Prolific Academic. The DCE consisted of twelve choice sets divided into two blocks. Each respondent was randomly assigned to one of the blocks and therefore every respondent answered six choice sets with two options each. Rather than directly offering an opt-out option as an alternative in the choice sets, we employed a dual response procedure. As Dhar and Simonson (2003) and von Haefen et al. (2005) argue, when the opt-out option is included in the choice sets, respondents often choose this option to avoid a heavy cognitive burden, in particular when they perceive the choice task as complex. In contrast, in the dual response procedure, respondents are first asked to choose their preferred option in a forced-choice task. Then, a free-choice task asks them to indicate if they would actually purchase the chosen option if it was available on the market. Typically, previous research has used a dual yes–no response to operationalize the opt-out option in the free-choice task. To increase precision, we decided to use a 4-point scale instead. In the follow-up question, respondents were thus asked to indicate on a scale from 1 ("very unlikely") to 4 ("very likely") how likely it is they would actually buy their preferred option if it was available on the market. Previous studies have found that the dual response procedure increases the predictive accuracy of a DCE (Dhar and Simonson, 2003; Schlereth and Skiera, 2016; Wlömert and Eggers,

[3] We applied the following exchange rates for countries which are not part of the Eurozone: Poland 1€ = 3 PLN; Romania 1€ = 3 RON, Sweden 1€ = 10 SEK, and UK 1€ = £1. In all Eurozone countries, the monetary amounts shown to respondents were identical, for Poland, Romania, Sweden and the UK; the monetary amounts were multiplied with the respective factors.

Table 2
Descriptions of variables, means and standard deviations (in parentheses).

		Pooled	DE	ES	FR	IT	PL	RO	SE	UK
adopter	=1 if a respondent has a smart thermostat.	0.20	0.08	0.23	0.15	0.27	0.21	0.32	0.10	0.23
		(0.40)	(0.27)	(0.42)	(0.36)	(0.44)	(0.41)	(0.47)	(0.30)	(0.42)
hi_inno	=1 if a respondent's score on innovativeness was above the median score in her/his country; =0 otherwise.	0.44	0.39	0.44	0.46	0.44	0.46	0.45	0.46	0.44
		(0.50)	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
hi_priv	= 1 if a respondent's score on privacy concerns was above the median score in her/his country; =0 otherwise.	0.44	0.47	0.46	0.48	0.38	0.38	0.38	0.47	0.49
		(0.50)	(0.50)	(0.50)	(0.50)	(0.49)	(0.49)	(0.49)	(0.50)	(0.50)
hi_aut	= 1 if a respondent's score on loss of autonomy was above the median score in her/his country; =0 otherwise.	0.43	0.38	0.42	0.45	0.44	0.35	0.48	0.47	0.46
		(0.50)	(0.49)	(0.49)	(0.50)	(0.50)	(0.48)	(0.50)	(0.50)	(0.50)
hi_env_id	= 1 if a respondent's score on environmental identity was above the median score in her/his country; =0 otherwise.	0.43	0.49	0.30	0.49	0.42	0.47	0.41	0.48	0.47
		(0.50)	(0.50)	(0.46)	(0.50)	(0.50)	(0.50)	(0.49)	(0.50)	(0.50)
age	Respondent's age in years.	41.81	42.92	41.44	42.66	42.62	40.45	39.87	41.20	43.11
		(12.92)	(12.91)	(11.67)	(13.53)	(11.72)	(13.15)	(12.85)	(13.44)	(13.73)
low_inc	=1 if a respondent's household net income is lower than the low-income quota of the country; =0 otherwise.	0.42	0.32	0.45	0.50	0.50	0.67	0.16	0.30	0.47
		(0.50)	(0.47)	(0.50)	(0.50)	(0.50)	(0.47)	(0.37)	(0.46)	(0.50)
hi_ed	=1 if a respondent holds a diploma equivalent to a bachelor's degree or above; =0 otherwise.	0.50	0.25	0.62	0.54	0.40	0.56	0.65	0.45	0.51
		(0.50)	(0.44)	(0.49)	(0.50)	(0.49)	(0.50)	(0.48)	(0.50)	(0.50)
familysize	Number of persons in a respondent's household.	2.68	2.24	3.10	2.53	3.11	3.17	2.96	2.09	2.75
		(1.35)	(2.17)	(1.55)	(1.41)	(2.28)	(2.69)	(1.60)	(1.17)	(2.39)
urban	=1 if a respondent lives in an urban area. =0 otherwise.	0.356	0.21	0.61	0.27	0.39	0.35	0.46	0.29	0.24
		(0.47)	(0.40)	(0.49)	(0.44)	(0.49)	(0.48)	(0.50)	(0.46)	(0.43)
house	=1 if a respondent lives in a detached or semi-detached house; =0 otherwise.	0.28	0.11	0.22	0.46	0.35	0.35	0.27	0.06	0.52
		(0.45)	(0.31)	(0.41)	(0.50)	(0.48)	(0.48)	(0.44)	(0.23)	(0.50)
owner	=1 if a respondent is the owner of her/his primary residence; =0 otherwise.	0.56	0.36	0.84	0.60	0.17	0.39	0.54	0.36	0.54
		(0.50)	(0.48)	(0.37)	(0.49)	(0.38)	(0.49)	(0.50)	(0.48)	(0.50)
Number of participants		5138	697	817	555	527	614	532	683	714

2016). In our case, we transformed this interval scale into a nominal variable: if a respondent answered "very unlikely", this was treated in the subsequent econometric analyses as having chosen the opt-out option.[4] Fig. 1 reproduces a scenario shown to respondents from the UK. Fig. 2

3.2. Econometric models for analyzing hypothetical adoption based on a DCE

We apply a mixed logit model (MXL), which—unlike a standard conditional logit model—does not rely on the Independence of Irrelevant Alternatives assumption. This model also allows for unobserved individual-specific heterogeneity of the parameters (Revelt and Train, 1998).

A sample of N respondents is required to answer to a series of T choice sets with J alternatives. For the *standard MXL*, the utility that respondent n gains from choosing alternative j in choice set t can be described as:

$$U_{njt} = \beta_n X_{njt} + \varepsilon_{njt}, \; n = 1, 2, \ldots, N, \quad j = 1, 2, \quad t = 1, 2, \ldots, T \tag{1}$$

where X_{njt} is a vector of smart thermostats attributes that are included in our DCE with a vector of parameters β_n. The error term ε_{njt} is assumed to follow an extreme-value Gumbel distribution. The MXL defines β_n as a vector of random parameters which varies among respondents and is characterized by the density function $f(\beta|\theta)$ with a vector of parameters θ (Train, 2003). In this paper, we assume that β_n follow a normal distribution.

The conditional probability of the observed sequence of choices for a known β_n can be described as:

$$P_n(\beta_n) = \prod_{t=1}^{T} \frac{\exp(\beta_n X_{nit})}{\sum_{j=1}^{J} \exp(\beta_n X_{njt})} \tag{2}$$

Because β_n is unknown, to obtain the unconditional probability, the above conditional probability needs to be integrated out, using the density function of β:

$$S_n(\theta) = \int P_n(\beta_n) f(\beta|\theta) d\beta \tag{3}$$

The log likelihood function is given by:

$$LL(\theta) = \sum_{n=1}^{N} \ln S_n(\theta) \tag{4}$$

Because no closed-form solution exists for this likelihood function, simulation methods are employed to estimate the parameters. The simulated log likelihood is obtained by running a simulation with R Halton draws (Train, 2003), which can be expressed as:

$$SLL(\theta) = \sum_{n=1}^{N} \ln \left\{ \frac{1}{R} \sum_{1}^{R} P_n(\beta^r) \right\} \tag{5}$$

where β^r is the r$^{\text{th}}$ draw from $f(\beta|\theta)$. We use $R = 500$.

In our case, the utility function for the *standard MXL* is specified as:

$$U_{njt} = \beta_1 * price + \beta_2 * subsidy + \beta_3 * savings + \beta_4 * display + \beta_5 * remote + \beta_6 * rec_{expert} + \beta_7 * rec_{provider} + \beta_8 * ASC + \varepsilon_{njt} \tag{6}$$

The variables *price, subsidy* (in Euros) and *savings* (in percentage of heating costs) are continuous.[5] *Display* is a dummy variable that equals 1 if the thermostat displays changes in energy consumption when the temperature is modified and 0 otherwise. Similarly, the dummy variable *remote* equals 1 if the thermostat can be controlled through a remote device and 0 otherwise. *rec_expert* and *rec_provider* are dummy variables, which equal 1 if the thermostat is recommended by an independent expert, or by the respondent's energy provider, respectively, and 0 otherwise. Note that we use recommendations by friends or colleagues as the baseline level (this is therefore not included in the model). Finally,

[4] As a robustness check, we also estimated a mixed logit model where we used the response categories "very unlikely" and "unlikely" to define the opt-out option. The findings derived from this model are very similar to those reported in Table 3, but the value of the likelihood function is lower.

[5] If respondents failed to report their heating costs or provided unreasonable figures, we estimated heating costs using information indicating the type and age of the building, the total living area, geographical location, the heating system, and thermal insulation measures which had been implemented in the past.

Table 3
Results of the pooled and country-specific standard MXLs on hypothetical adoption.

	Pooled	DE	ES	FR	IT	PL	RO	SE	UK
Panel A. Means of parameter estimates									
price	−0.007***	−0.008***	−0.008***	−0.007***	−0.007***	−0.007***	−0.006***	−0.007***	−0.008***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
subsidy	0.310***	−0.001	0.001	0.004***	0.004***	0.007***	0.008***	0.003***	0.002**
	(0.000)	(0.461)	(0.566)	(0.002)	(0.000)	(0.000)	(0.000)	(0.007)	(0.037)
savings	0.003***	0.312***	0.213***	0.231***	0.173***	0.227***	0.189***	0.236***	0.175***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
display	0.250***	0.467***	0.389***	0.312***	0.345***	0.445***	0.502***	0.540***	0.391***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
remote	0.194***	0.296***	0.536***	0.301***	0.425***	0.623***	0.619***	0.627***	0.345***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
rec_expert	0.384***	0.448***	0.347***	0.355***	0.459***	0.118*	0.689***	0.301***	0.150***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.072)	(0.000)	(0.000)	(0.010)
rec_provider	0.435***	0.258***	0.317***	0.348***	0.416***	−0.111*	0.665***	0.137***	0.229***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.064)	(0.000)	(0.041)	(0.000)
ASC	−7.252***	−7.389***	−12.302***	−6.205***	−7.327***	−11.054***	−9.490***	−9.042***	−10.066***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loglikelihood	−24,079.85	−2770.71	−3566.63	−2554.85	−2392.14	−2877.12	−2272.29	−2963.08	−3169.85
Number of observations	99,306	12,960	15,822	11,178	9828	12,780	10,278	13,068	13,392
Number of participants	5517	720	879	621	546	710	571	726	744
Panel B. WTP estimates									
	Pooled	DE	ES	FR	IT	PL	RO	SE	UK
subsidy	0.45	ns	ns	0.50	0.66	1.03	1.29	0.43	0.25
savings	29.08	40.60	27.31	31.79	25.77	34.15	31.55	31.68	22.11
display	57.49	60.78	49.94	42.88	51.46	67.07	83.15	71.45	49.33
remote	65.12	38.15	68.86	41.48	63.47	93.79	102.80	82.54	43.54
rec_expert	46.46	58.40	44.50	48.89	68.59	17.84	114.70	39.38	19.04
rec_provider	37.46	33.37	40.66	47.92	62.09	−16.74	111.41	18.16	28.91

p-values in parentheses.
** $p < 0.05$
*** $p < 0.01$.

the variable *ASC* is an alternative-specific constant that accounts for the systematic effect of choosing the opt-out option (Scarpa et al., 2005).

The marginal WTP for an attribute *x* can be estimated as:

$$\widehat{WTP}_x = -\frac{\widehat{\beta}_x}{\widehat{\beta}_p} \tag{7}$$

where $\widehat{\beta}_x$ is the estimated random parameter associated with attribute x, and $\widehat{\beta}_p$ is the estimated price parameter.

To model heterogeneity in preferences across individuals explicitly and to assess the effects of privacy concerns, individual innovativeness, and environmental identity on respondents' WTP for technology attributes we also estimate, in addition to the *standard MXL*, an *attitude-interaction model* wherein we interact these attitudes with preferences for selected technology attributes.

For both the *standard MXL* and the *attitude-interaction models,* we estimate two types of models: (i) a *pooled model*, which includes observations for all countries, and (ii) *country-specific models*, which include observations of particular countries only. Unlike the *pooled model*, the *country-specific models* do not require the coefficients to be identical across countries.

3.3. Econometric models for estimating stated past adoption

In addition to the DCE, which provides information on consumers' trade-offs between attributes, we also estimate a binary response model providing information on factors related to stated past adoption of smart thermostats in general. To construct the dichotomous dependent variable, we use survey information on respondents' stated past adoption of smart thermostats. ("*Do you have a smart thermostat (*i.e. *a heating control device with remote temperature control) installed in your primary residence?*"). Respondents answering 'Yes' were considered adopters.

The following equations capture the formal binary response model:

$$y_i = \begin{cases} 1 & \text{if} \quad y_i^* > 0 \\ 0 & \text{otherwise} \end{cases} \tag{8}$$

$$y_i^* = \alpha Z_i + \mu_i, \tag{9}$$

where i denotes the individual household, α is a vector of parameters, y_i^* captures the latent utility gained from the adoption of smart thermostats, and Z_i is a vector of covariates reflecting socio-demographic information and individual attitudes (here: innovativeness, privacy and autonomy concerns, and environmental identity). That is, a respondent adopts a smart thermostat if the associated utility gain exceeds a threshold level (here: zero). The error term μ_i is assumed to be normally distributed, leading to the familiar Probit model.

As for the MXL, we estimate a *pooled model* together with *country-specific models*. The dependent variables and covariates are described in Table 2 and further explained in Section 3.4. Appendix A provides the items used in the questionnaire.

3.4. Survey

Our online survey was fielded in July and August 2018 among households in the selected eight European countries. We used the household panel provided by NORSTAT, an international market research company. NORSTAT recruited participants via quota sampling to gather representative data on each surveyed country according to gender, age (between 18 and 65 years), income, and

Table 4
Results for interaction terms in attitude-interaction models on hypothetical adoption (pooled and country-specific models).

	Pooled	DE	ES	FR	IT	PL	RO	SE	UK
Means of parameter estimates									
hi_inno*savings	0.064***	0.073	0.062**	0.196***	0.080**	0.037	0.089***	0.018	0.069**
	(0.000)	(0.120)	(0.039)	(0.000)	(0.010)	(0.309)	(0.002)	(0.686)	(0.037)
hi_inno*_display	0.194***	−0.071	0.130	0.255	0.369***	0.244*	0.394**	0.259	0.243*
	(0.000)	(0.662)	(0.277)	(0.112)	(0.007)	(0.102)	(0.013)	(0.134)	(0.084)
hi_inno*remote	0.513***	0.606***	0.323***	0.827***	0.323**	0.669***	0.244*	0.853***	0.653***
	(0.000)	(0.000)	(0.007)	(0.000)	(0.024)	(0.000)	(0.092)	(0.000)	(0.000)
hi_priv*remote	−0.243***	−0.499***	0.063	−0.086	−0.015	−0.569***	0.135	−0.516***	−0.332**
	(0.000)	(0.002)	(0.597)	(0.570)	(0.918)	(0.001)	(0.359)	(0.010)	(0.013)
hi_env_id*savings	0.056***	0.113**	0.041	0.151***	0.011	0.066*	−0.016	0.125***	0.123***
	(0.000)	(0.015)	(0.197)	(0.002)	(0.735)	(0.072)	(0.558)	(0.004)	(0.000)
hi_env_id*display	0.064	−0.024	0.141	−0.219	0.049	0.278*	0.136	0.375**	0.053
	(0.146)	(0.878)	(0.273)	(0.168)	(0.718)	(0.061)	(0.394)	(0.031)	(0.705)
Loglikelihood	−24,470.97	−2965.20	−3632.89	−2576.00	−2488.86	−2692.13	−2582.87	−3028.86	−3462.91
Number of observations	92,484	12,546	14,706	9990	9486	11,052	9576	12,276	12,852
Number of participants	5138	697	817	555	527	614	532	682	714

p-values in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

regional population distribution. In total, 5517 respondents completed the survey.[6]

The survey started with a set of screening questions to make sure that the required quotas were met. Respondents then participated in the DCE with smart thermostats. The DCE was then followed by some questions pertaining to the heating system installed and the dwelling (used to calculate heating costs when necessary), and with a question on stated past adoption of a smart thermostat. Our questionnaire also included scales to capture consumer innovativeness (Manning et al., 1995), privacy concerns (Chang et al., 2016), autonomy concerns (Schweitzer and van den Hende, 2016), and environmental identity (Whitmarsh and O'Neill, 2010). Finally, we collected respondents' socio-demographic information. Since all measures were collected within a single survey and could therefore be subject to common method bias, we followed the advice of Podsakoff et al. (2003) and clearly separated the dependent variables (measured early on in the survey) from the independent variables (individual attitudes were measured late in the survey after collecting data on housing characteristics). Moreover, respondents were explicitely told that their responses would remain anonymous. Finally, in the DCE, common method bias is reduced as attribute levels (independent variables) are determined by the experimental design (van Rijnsoever et al., 2012, 2017).

Table B1 in Appendix B presents the descriptive statistics for the sample used in this paper together with the descriptive statistics with national averages. Among the eight countries, the median age of our sample is higher than the national statistics in France and the UK. The median age of our sample in the other six countries are a bit lower than the national statistics. The share of women in our sample is close to the national statistics in all eight countries.[7]

4. Results

We first report the results of the *standard MXL*. We then show the findings from estimating the *attitude-interaction model*. Then, we display the findings derived from the Probit models on stated past smart thermostat adoption. For all these models, we present the findings from estimating the *pooled model* and the *country-specific models*. To test for differences between countries, we also estimated models which included country-interaction terms in the *pooled model* (using France as the base country because the findings for France were most similar to those of the *pooled model)*. In Tables B5 and B6 in Appendix B we report the findings derived from the models with the country-interaction terms for the mixed logit and the Probit models, respectively. Finally, we discuss the results in light of the proposed research framework and of the literature.

4.1. Standard MXL

Table 3 presents the results of the MXL for each country. Panel A in Table 3 summarizes the means of the parameter estimates and Table B3 in Appendix B presents the standard deviations of the parameter estimates. Panel B in Table 3 presents the WTP estimates generated using Eq. (7). The results reported in Table B3 imply that most of the standard deviations of the parameter estimates are statistically significant, suggesting heterogeneity of these parameters across respondents. More formally, for all models we conducted likelihood-ratio tests on the joint significance of the standard deviations. The small p-values ($<$0.01) associated with the test statistics support the use of MXL.

As expected, the parameter estimates associated with the *price* variable are negative and statistically significant in the *pooled model* and in all eight *country-specific models*. A higher price diminishes respondents' willingness to choose a smart thermostat.

The means of the parameter estimates of *subsidy* are statistically significant (p<0.1) and positive in the *pooled model* and in all *country-specific models*, except for in Spain and Germany. The results reported in Panel B suggest that respondents' valuations of subsidies vary across countries. Receiving an additional 1€ as a subsidy will raise a respondent's WTP by 1.03€ on average in Poland and 1.29€ in Romania. In

[6] Across all countries, 58% of participants who responded to the survey invitation completed the entire questionnaire. Compared with respondents who completed the questionnaire, those who did not complete the questionnaire were more likely to be women, from richer households in France, Germany and the UK, and from poorer households in Poland. Information on panel members who did not respond to the invitation are not available.

[7] Descriptive statistics are reported for the sample used to estimate the attitude-interaction models (Table 4) and the Probit adoption models (Table 5). Because some participants failed to answer the items pertaining to innovativeness, the samples for these models are slightly smaller than in the standard MXLs (Table 3).

Table 5
Results of Probit models for stated past adoption (marginal effects).

	Pooled	DE	ES	FR	IT	PL	RO	SE	UK
hi_inno	0.066***	0.071***	0.115***	0.104***	−0.001	0.012	0.073*	−0.003	0.111***
	(0.000)	(0.002)	(0.000)	(0.001)	(0.987)	(0.725)	(0.088)	(0.890)	(0.001)
hi_priv	0.000	−0.022	−0.022	−0.013	0.052	−0.011	−0.002	0.014	−0.057*
	(0.969)	(0.344)	(0.495)	(0.694)	(0.217)	(0.769)	(0.960)	(0.633)	(0.098)
hi_aut	−0.009	−0.006	0.020	0.036	−0.102**	0.041	−0.023	−0.036	0.027
	(0.419)	(0.805)	(0.534)	(0.282)	(0.011)	(0.299)	(0.583)	(0.192)	(0.436)
hi_env_id	0.037***	0.005	0.036	−0.012	0.084**	0.014	0.014	0.053**	0.100***
	(0.001)	(0.800)	(0.266)	(0.692)	(0.042)	(0.684)	(0.751)	(0.017)	(0.001)
age	−0.002***	0.000	−0.002*	−0.001	−0.002	−0.002	−0.003*	−0.000	−0.003**
	(0.000)	(0.857)	(0.078)	(0.253)	(0.164)	(0.179)	(0.082)	(0.778)	(0.011)
low_inc	−0.065***	−0.032	−0.087***	−0.017	−0.062	−0.127***	−0.043	−0.059**	−0.022
	(0.000)	(0.143)	(0.004)	(0.620)	(0.136)	(0.001)	(0.458)	(0.010)	(0.510)
hi_ed	0.018*	0.005	0.027	0.022	0.012	0.020	−0.002	−0.050**	0.101***
	(0.097)	(0.807)	(0.390)	(0.481)	(0.773)	(0.547)	(0.961)	(0.028)	(0.001)
familysize	0.003*	−0.008	0.012	0.014	0.013*	−0.022**	0.004	0.013	0.014**
	(0.061)	(0.352)	(0.128)	(0.188)	(0.065)	(0.047)	(0.597)	(0.108)	(0.045)
urban	0.037***	0.015	0.047	0.086**	0.029	−0.023	0.067	0.044	0.048
	(0.003)	(0.585)	(0.108)	(0.036)	(0.485)	(0.537)	(0.109)	(0.127)	(0.196)
house	−0.007	−0.025	0.007	0.025	0.029	0.038	−0.087*	−0.041	−0.008
	(0.572)	(0.324)	(0.845)	(0.508)	(0.498)	(0.410)	(0.081)	(0.222)	(0.776)
owner	0.093***	0.081***	0.124***	0.078**	0.036	0.136***	0.026	0.119***	0.099***
	(0.000)	(0.001)	(0.000)	(0.040)	(0.484)	(0.002)	(0.567)	(0.000)	(0.002)
Country dummies	YES								
Loglikelihood	−2316.67	−177.74	−408.42	−217.28	−294.00	−294.05	−325.55	−200.98	−333.98
Number of participants	5138	697	817	555	527	614	532	682	714

p-values in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

Germany and Spain, the subsidy was not found to affect respondents' choices. Results reported in Table B3 in Appendix B suggest that, compared with those from France, respondents from Germany and Spain value a subsidy less while respondents from Poland and Romania value a subsidy more, while no difference to those from France was found for respondents from Sweden and the UK.

Higher heating cost savings boost respondents' willingness to buy a smart thermostat at statistically significant levels in the *pooled model* and in all *country-specific models*, implying that respondents typically value heating cost savings associated with smart thermostats. In our sample, respondents' WTP for a 1% decrease in heating costs ranges from 22.11€ in the UK to 40.60€ in Germany. Compared with those from France, only respondents from Germany were found to have stronger preferences for heating cost savings, while respondents from Spain, Italy, Romania and the UK have weaker preferences for heating cost savings (see Table B3 in Appendix B). This variation may reflect differences in energy expenditures (i.e. household fuel prices, heating needs), household income, or preferences (e.g. time discounting or risk preferences).

The means of the parameter estimates of *display* and *remote* are statistically significant and positive in the *pooled model* and in all *country-specific models*. The WTP for the feature "display of changes in energy consumption" ranges from 42.88€ in France to 83.15€ in Romania. Compared with that for France, the WTP for *display* is higher in all countries, but this difference is statistically significant for Germany, Poland, Romania and Sweden only (see Table B3 in Appendix B). Likewise, we find that the WTP for *remote* ranges from 38.15€ in Germany to 102.80€ in Romania. Compared with those in France, respondents from all but two countries appear to value remote control functionalities more highly (see Table B2 in Appendix B). For Germany and the UK, we found no difference compared with France.

The means of the parameters associated with *rec_provider* and *rec_expert* are positive and statistically significant in the *pooled model* and in all *country-specific models* except for *rec_provider* in Poland. Thus, respondents generally believe that when it comes to the purchase of smart thermostats, energy providers and independent energy experts offer more valuable advice than friends and colleagues do. These findings are therefore in line with H5 and with the extant literature (e.g. Achtnicht, 2011; Achtnicht and Madlener, 2014). In most countries, there appears to be little difference in the valuation of advice offered by energy providers and energy experts. For Germany, Poland and Sweden though, Wald-tests for the means provide evidence that advice offered by energy experts is more effective than advice offered by energy providers (at $p<0.05$). In addition, our estimates for the WTP suggest that such advice is valued rather highly, especially in Romania and Italy. We find recommendations provided by energy providers (relative to friends and colleagues) to be valued higher in Romania and lower in Poland and Sweden compared with those in France (see Table B3 in Appendix B). For the other countries, the difference when compared with those in France was not found to be statistically significant. Similarly, compared with respondents from France, recommendations provided by energy experts seem relatively more important for respondents from Romania but less important for respondents from Poland and the UK.

Finally, the parameter estimates associated with the *ASC* are negative and statistically significant in the *pooled country model* and in all *country-specific models,* suggesting that respondents systematically prefer to consider purchasing a smart thermostat with the attributes and levels shown in the DCE rather than not purchasing such a device.

4.2. MXL with interaction terms between individual attitudes and technology attributes

Table 4 presents the findings derived from the *attitude-interaction models*, focusing on the interaction terms for innovativeness, privacy concerns, and environmental identity with the technology attributes heating cost savings, display of changes in energy consumption, and remote temperature control. The full set of results is reported in Table B4

Table 6
Summary of hypothesis tests.

	Pooled	DE	ES	FR	IT	PL	RO	SE	UK
Hypotheses									
Effects of attributes on adoption									
H1a (price)	✓	✓	✓	✓	✓	✓	✓	✓	✓
H1b (subsidy)	✓	n. s.	n. s.	✓	✓	✓	✓	✓	✓
H2 (heating cost savings)	✓	✓	✓	✓	✓	✓	✓	✓	✓
H3 (display)	✓	✓	✓	✓	✓	✓	✓	✓	✓
H4 (remote control)	✓	✓	✓	✓	✓	✓	✓	✓	✓
H5 (recommendation expert)	✓	✓	✓	✓	✓	✓	✓	✓	✓
H5 (recommendation provider)	✓	✓	✓	✓	✓	X	✓	✓	✓
Effects of individual attitudes on adoption									
H6a (innovativeness)	✓	✓	✓	✓	n. s.	n. s.	✓	n. s.	✓
H6b (innovativeness – heating cost savings)	✓	n. s.	✓	✓	✓	n. s.	✓	n. s.	✓
H6b (innovativeness – display)	✓	n. s.	n. s.	n. s.	✓	✓	✓	n. s.	✓
H6b (innovativeness – remote control)	✓	✓	✓	✓	✓	✓	✓	✓	✓
H7a (privacy concerns)	n. s.	n. s.	n. s.	n. s.	n. s.	n. s.	n. s.	n. s.	✓
H7b (privacy concerns – remote control)	✓	✓	n. s.	n. s.	n. s.	✓	n. s.	✓	✓
H8 (autonomy)	n. s.	n. s.	n. s.	n. s.	✓	n. s.	n. s.	n. s.	n. s.
H9a (environmental identity)	✓	n. s.	n. s.	n. s.	✓	n. s.	n. s.	✓	✓
H9b (environmental identity – heating cost savings)	✓	✓	n. s.	✓	n. s.	✓	n. s.	✓	✓
H9b (environmental identity – display)	n. s.	n. s.	n. s.	n. s.	n. s.	✓	n. s.	✓	n. s.

✓ = results support hypothesis, *X* = results contradict hypothesis, n. s. = results are not statistically significant.

in Appendix B.[8]

We first consider interaction between innovativeness and the technology attributes. For the *pooled model,* the parameter estimates are positive and statistically significant for interactions between innovativeness and *savings, display,* and *remote*. Thus, more innovative respondents were found to have statistically significantly stronger preferences for heating cost savings as well as for the availability of display and remote control functionalities of smart thermostats than less innovative respondents did. The results for the *country-specific models* suggest some heterogeneity across countries. More specifically, while the interaction term for innovativeness and *remote* is found to be statistically significant in all *country-specific models*, for *savings*, this is the case in five *country-specific models* (i.e. Spain, France, Italy, Romania and the UK), and for *display* in four *country-specific models* (i.e. Italy, Poland, Romania, and the UK). The results reported in Table B5 in Appendix B suggest that, compared with the base country France, the reinforcing moderating effect of innovativeness on respondents' valuation of heating cost savings is weaker in Germany, Italy, Poland, Sweden and the UK. For *display*, the moderating effect of innovativeness appears to differ from that in France in Germany only, where this effect is found to be smaller. For *remote*, the moderating effect of innovativeness is weaker in Germany, Spain, Italy, and Romania than in France.

Next, we consider interaction between privacy concerns and remote control functionalities. For the *pooled model* and for half the *country-specific models* (i.e. for Germany, Poland, Sweden, and the UK), we find that privacy concerns have a negative effect on preferences for the availability of remote temperature control of smart thermostats. In addition, we conclude that the negative moderating effect of privacy concerns on the adoption of smart thermostats is stronger in Poland, Romania and Sweden than in France (see Table B5 in Appendix B).

Finally, we analyze interaction between environmental attitudes and environmentally related attributes of smart thermostats. For the *pooled model* and most *country-specific models* (i.e. Germany, France, Poland, Sweden, and the UK) we find that environmental identity has a statistically significant positive effect on respondents' valuation of heating cost savings. Moreover, in the *country-specific models* for Poland and Sweden, but not in the *pooled model*, respondents with stronger environmental identities have a stronger preference for display of changes in energy consumption. In addition, we find the reinforcing moderating effect of environmental attitudes on respondents' valuation of heating cost savings to be weaker in Italy, Poland, Romania, and Sweden than in France. For the other countries, we find no difference in valuation (see Table B5 in Appendix B). Likewise, for *display*, the moderating effect of environmental attitudes in France does not appear to differ from the results found in any of the other countries in our sample.

4.3. Probit model for stated past adoption of smart thermostats

To complement the DCE analyses, we also investigated the effects of individual attitudes on stated past adoption of smart thermostats. In addition to the individual attitudes considered in the MXL (i.e. innovativeness, privacy concerns, and environmental identity), this analysis comprises concerns about loss of autonomy. The results of estimating Probit models on the pooled sample and country-specific samples appear in Finally, homeowners were statistically significantly more likely to have purchased smart thermostats in the *pooled model* and in all *country-specific models* but those for Italy and Romania.

Table 1. To facilitate the interpretation of the findings, Finally, homeowners were statistically significantly more likely to have purchased smart thermostats in the *pooled model* and in all *country-specific models* but those for Italy and Romania.

Table 1. displays the marginal effects and, for dummy variables, the discrete probability effects. To test for differences across countries, we also ran a pooled model with country interaction terms for the individual attitude factors, again using France as the base country. In Table B6 in Appendix B we document the findings derived from this model.

The results suggest that respondents with high individual innovativeness are more likely to adopt smart thermostats in the *pooled model* and in all *country-specific models* except in Italy, Poland, and Sweden. On average, the likelihood that a respondent has a smart thermostat is about 6.5 percentage points higher when she/he belongs to the group characterized by high rather than low innovativeness. This effect is highest for Spain (11.5 percentage points), the UK (11.1 percentage points) and France (10.4 percentage points). Compared with its strength in France, the effect of innovativeness on stated past adoption of thermostats is

[8] To mitigate potential collinearity problems between the ASC and individual attitudes, we treat the ASC as a fixed parameter in this model.

weaker in Italy, Poland, and Sweden, while no difference could be found for the other countries in the sample (see Table B6 in Appendix B).

Privacy concerns are negatively related to stated past adoption of smart thermostats in the *pooled model* and in most *country-specific models* but significantly so only in the UK. In addition, the effects of privacy concerns do not appear to differ between France and the other countries in our sample (see Table B6 in Appendix B).

Similarly, concerns about loss of autonomy are found to be statistically significant for Italy only. Respondents belonging to the *hi_aut* group in Italy are 10.2 percentage points less likely to have purchased a smart thermostat. Similarly, compared with its effect in France, we found concerns about loss of autonomy on stated past adoption of a smart thermostat to be stronger in Italy, while we found no difference for the other countries (see Table B6 in Appendix B).

Finally, respondents with strong environmental identities were more likely to adopt smart thermostats in the *pooled model* and in the *country-specific models* in Italy, Sweden and the UK.

We now briefly turn to our findings pertaining to socio-demographic characteristics. Older respondents appeared more reluctant to have purchased smart thermostats in the *pooled model* and in the *country-specific models* for Spain, Romania, and the UK.

In the *pooled model* and the *country-specific models* for Spain, Poland, and Sweden, low-income respondents were less likely to have purchased smart thermostats. In comparison, for *education, familysize, urban*, and living in a detached or semi-detached *house*, we find only a few cases where the parameter estimates turned out to be statistically significant. Finally, homeowners were statistically significantly more likely to have purchased smart thermostats in the *pooled model* and in all *country-specific models* but those for Italy and Romania.

4.4. Discussion of results

In this section we relate the empirical findings to our proposed research framework and to the literature. Table 6 summarizes the results of the hypothesis tests in the pooled models and the country-specific models.

4.4.1. Smart thermostat attributes

Results from the mixed logit analysis generally support H1a and H1b on the effects of financial cost attributes. Price was found to be negatively associated and subsidy to be positively associated with hypothetical smart thermostat adoption. These results are also consistent with those reported in previous studies that find that financial support measures increase the WTP for energy-efficient appliances (e.g. Datta and Gulati, 2014) and heating systems (e.g. Achtnicht, 2011; Achtnicht and Madlener, 2014; Alberini and Bigano, 2015; Olsthoorn et al., 2017). The low (or no) WTP for subsidies may result from respondents' associating subsidies with inferior product quality (or maturity), echoing the findings obtained in the DCE conducted by Revelt and Train (1998) on the effects of rebates for energy-efficient appliances.

For heating cost savings, we found support for H2. When these savings increase, smart thermostat adoption also increases. Previous studies employing DCEs have also found that energy cost savings increase hypothetical adoption of smart meters (Pepermans, 2014), new heating systems (e.g. Achtnicht, 2011; Achtnicht and Madlener, 2014) and energy-efficient household appliances (e.g. Li et al., 2016; Newell and Siikamäki, 2014).

Our results also indicate that the availability of feedback (display of changes in energy consumption) and of remote control functionalities are generally positively related to hypothetical smart thermostat adoption, thus offering support for H3 and H4. These findings are also in line with those obtained for other smart home energy devices by Ford et al. (2017), Kaufmann et al. (2013) and Pepermans (2014). Perhaps the high WTP for both of these attributes in Poland and Romania can be explained by relatively poor access to internet-related services (i.e. internet access, internet purchases and cloud services) in these countries compared with access in the other countries in our sample (Eurostat, 2019). Previous research finds scarcity to positively affect perceived value (Lynn, 1992) and especially the WTP for rare attributes (Robinson et al., 2016); this may explain the high WTP for "smart" features such a remote control and display of change in energy consumption in Romania and Poland. Overall, the very high WTP found across attributes in Romania are somewhat surprising but consistent with a previous study conducted in the same eight countries that also found WTP for new residential heating systems to be highest in Romania (Olsthoorn et al., 2017). We speculate that high WTP in Romania might be driven by the high level of energy prices in relation to income; the ensuing higher weight of energy costs in household spending may lead to higher valuation of features that help reduce energy consumption.

For product recommendations, we found that respondents generally believe that energy providers and independent energy experts offer more valuable advice than friends and colleagues for the purchase of smart thermostats. These findings are in line with H5 and with the extant literature (e.g. Achtnicht, 2011; Achtnicht and Madlener, 2014).

4.4.2. Individual attitudes

Results from the pooled models show that consumer innovativeness positively influences stated past adoption and that more innovative consumers are also more likely to value technical attributes (heating cost savings as well as availability of display or remote control functionalities). While the parameter estimates were not always statistically significant in single-country models, the findings generally support H6a and H6b and are also in line with the literature where studies find a positive correlation between consumer innovativeness and the adoption of new technologies (e.g. Foxall and Bhate, 1999; Hirunyawipada and Paswan, 2006; Jackson et al., 2013; Liébana-Cabanillas et al., 2018; Slade et al., 2015).

Regarding privacy concerns, we found that the effects on stated past adoption were statistically significant only in the UK, therefore providing only weak empirical support for H7a. On the other hand, as hypothesized in H7b, privacy concerns significantly reduced the attractiveness of remote control functionalities in the *pooled model* and in half the countries in the study. These findings are similar to those in Pepermans (2014) that document the negative effects of privacy concerns on the adoption of smart meters.

Concern about loss of autonomy was found to reduce stated past adoption only in Italy, thereby providing limited support for H8. The result for Italy is consistent with previous literature where studies find that using smart products may reduce consumer freedom to choose or act autonomously (e.g. Rijsdijk and Hultink, 2003; Schweitzer and Van den Hende, 2016).

Regarding pro-environmental attitudes, we found significant positive effects of environmental identity on stated past adoption in the *pooled model* and in three of the eight countries, therefore providing support for H9a. The reinforcing moderating effects of environmental identity on the acceptance of environmentally related thermostat attributes were found to be quite strong for heating cost savings (significant in the *pooled model* and in three of the eight countries), but less so for the availability of energy consumption feedback (significant in only two countries), therefore generally providing supporting evidence for H9b. These findings are also in line with empirical findings for energy-efficient technology adoption reported in the literature (e.g. Mills and Schleich, 2012; Ramos et al., 2015; Schleich et al., 2019).

4.4.3. Socio-demographic characteristics

The Probit models further provide consistent results across the pooled and single-country models for relationships between past adoption of smart thermostats and several socio-demographic characteristics. In particular, finding age to be negatively related to smart thermostat adoption is in line with results of previous studies that find older people to be less likely to adopt energy cost-saving technologies, such as energy-efficient lighting (e.g. Ramos et al., 2015; Schleich et al., 2019). Carlsson-Kanyama et al. (2005) argue that older people generally know less about energy-efficient technologies and also form weaker preferences for state-of-the-art technologies than younger people. Similarly, finding a negative relationship between income and smart thermostat adoption is consistent with Rogers's (2003) characterization of early adopters, with the thrust of empirical studies of energy-efficient technology adoption (e.g. Ramos et al., 2015; Schleich et al., 2019), and with Balta-Ozkan et al. (2013), who argue that a high purchase price may discourage low-income households from buying smart home technologies. Finally, consistent with the so-called landlord–tenant problem,[9] and bearing similarities to results obtained from empirical studies of energy-efficient technology adoption (e.g. Schleich et al., 2019), we generally found homeowners to be more likely to have purchased smart thermostats than tenants.

5. Conclusion

In this section, we first discuss the academic and practical implications of this research before turning to limitations and suggestions for future research.

5.1. Academic implications

In this study, we conducted a large-scale survey to analyze adoption of smart thermostats in eight European countries. Studying the adoption of these devices is particularly important because such devices are examples of rapidly developing smart home devices and also have the potential to contribute to reducing energy consumption.

We proposed a theoretical framework for understanding smart thermostat adoption that includes both thermostat characteristics (such as heating cost savings, remote temperature control, and energy consumption feedback) and individual attitudes such as consumer innovativeness, privacy and autonomy concerns, and environmental attitudes. Our analyses enable us to study both the independent effects of these two sets of factors as well as their interactions.

Our findings generally provide support for this research framework. All hypotheses received at least weak empirical support, but with some heterogeneity across countries. For the thermostat attributes, we found evidence that respondents in all countries value the technology attributes of smart thermostats such as heating cost savings, remote temperature control and display of changes in energy consumption. In addition, in most countries, providing subsidies increased the probability that respondents would choose a smart thermostat. Finally, recommendations from friends and colleagues were generally found to be less effective than recommendations from independent energy experts or energy providers.

For the individual attitudes, we found that consumer innovativeness positively influences stated past adoption of smart thermostats and that it moderates (reinforces) the relationship between technical attributes and the hypothetical adoption of smart thermostats such that more innovative respondents tend to value heating cost savings, remote temperature control, and display of changes in energy consumption more highly than less innovative respondents. Privacy concerns were found to lower stated past adoption and to weaken the relationship between remote control functionalities and hypothetical adoption of smart thermostats. Concerns about loss of autonomy were also found to impede past adoption of smart thermostats, but only in one country (Italy). Finally, environmental identity was found to be positively associated with stated past adoption of smart thermostats while moderating the relationship between environmentally related attributes and hypothetical adoption of smart thermostats such that respondents with strong environmental identities value heating cost savings and the display of changes in energy consumption more highly than respondents with weak environmental identities.

From a methodological point of view, studying the adoption of relatively new products is often difficult. In new markets, conventional approaches such as the hedonic price method (e.g. Gandal, 1994) are often impossible to use. Other approaches such as fuzzy TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) are sometimes used (e.g. Sianaki and Masoum, 2013) but most research relies on surveys of consumers' stated intentions to adopt a new product. Such surveys have been shown to be prone to social desirability biases, leading to the well-known attitude–behavior gap, which is particularly prevalent for sustainable products (Vermeir and Verbeke, 2006). To address this issue, we decided to use a combination of DCE and of stated past adoption. The DCE provides the advantage of mirroring a (potentially future) market where all respondents have access to necessary information; it also makes it possible to observe respondents' trade-offs between product attributes (Louviere, 1992). DCEs may however suffer from hypothetical bias. By combining the DCE with an analysis of stated past adoption, we benefit from the advantages of both approaches. That the results are generally consistent across both approaches lends credence to the appropriateness of this combination of methods for studying adoption.

5.2. Practical implications

From a public policy standpoint, the findings derived in this paper suggest that providing financial incentives, such as a rebate program, is an effective way to accelerate the diffusion of smart thermostats. Thus, contingent on the outcome of cost–benefit analyses, such rebates may be recommended as a cost-efficient strategy for achieving energy efficiency and hitting climate targets. Our findings further encourage the provision of expert recommendations to enhance the adoption of smart thermostats. In most countries, such recommendations could also be offered by utilities, yet their advice generally appears less effective than advice given independently by energy experts.

From a business standpoint, our findings further suggest that companies should target innovative and environmentally concerned consumers to increase sales of smart thermostats. While developing and promoting these products, technology providers should pay special attention to consumer privacy concerns. Privacy concerns may be particularly relevant for emerging applications of artificial intelligence and machine learning for smart energy devices that involve, for

[9] If landlords pay for investments but tenants benefit from lower energy expenditures, landlords may decide not to invest in energy-efficiency measures unless they can pass on the extra costs through rent.

example, detailed user profiles and temperature preferences. In contrast, autonomy concerns appear to be a less influential issue. The heterogeneity in findings across consumers within and across countries suggests that the design of control systems and user interfaces for smart thermostats should allow users to choose their preferred functionalities flexibly.

5.3. Limitations and future research

Our study is subject to limitations that may be tackled in future research. The DCE relies on the assumption that participants perceive the smart thermostats offered in the context of the experiment to be compatible with their heating systems (this compatibility was explicitly mentioned in the DCE scenario). In practice, this may be challenging, because smart thermostats are not compatible with all heating systems. For our DCE we further assumed that the use of smart thermostats to control energy use and costs would not involve any compromise on comfort. In practice, there may be a trade-off between comfort and other attributes, which future studies should explore. Similarly, while our study found sources of recommendation to affect technology choice, future studies could focus on the channels (internet, word-of-mouth, social networks) used to obtain such recommendations (Trusov et al., 2009). Further, the attributes in our DCE design are assumed to vary independently and therefore our study does not account for the joint effects of several types of recommendations; this would be an interesting issue for future research.

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Appendices

Appendix A. Individual attitude scales

Consumer innovativeness (adapted from Manning et al., 1995)
Q: Please rate your level of agreement with the following statements.

1 I often seek out information about new products.
2 I frequently look for new products and services.
3 I am continually seeking new product experiences.
4 I take advantage of the first available opportunity to find out about new and different products.
5 I am typically among the first in my circle of friends to try out new things.

(Five-point scale ranging from "strongly disagree" to "strongly agree".)

Environmental identity (adapted from Whitmarsh and O'Neill, 2010)
Q: Please rate how much you agree with the following statements.

1 To save energy is an important part of who I am.
2 I think of myself as an energy conscious person.
3 I think of myself as someone who is very concerned with environmental issues.
4 Being environmentally friendly is an important part of who I am.

(Five-point scale ranging from "strongly disagree" to "strongly agree".)

Privacy concern (adapted from Chang et al., 2015)
Q: Please rate your level of agreement with the following statements.

1 I am concerned that the services I use through the smart thermostat may share my personal information with other parties.
2 I am concerned about providing personal information to the service provider through the smart thermostat, because it could be used in a way I did not foresee.

(Five-point scale ranging from "strongly disagree" to "strongly agree".)

Autonomy concerns (adapted from Schweitzer and van den Hende, 2016)

1 A smart thermostat makes decisions that I would prefer to make myself.
2 I fear that a smart thermostat could take actions that I dislike.
3 A smart thermostat reduces my possibilities to decide what temperature (or level of comfort) I would like to have at home.

(Five-point scale ranging from "strongly disagree" to "strongly agree".)

Appendix B. Additional results

Table B1
Table B2
Table B3
Table B4
Table B5
Table B6

Table B1
Descriptive sample statistics.

Country	Median age†		Gender (% female)	
	Sample	Population	Sample	Population
DE	44	46.0	49.7%	50.6%
ES	41	43.6	51.2%	51.0%
FR	43	41.6	50.4%	51.6%
IT	43	46.3	51.1%	51.3%
PL	39	40.6	49.2%	51.6%
RO	40	42.1	49.7%	51.1%
SE	40	41.2	50.6%	49.8%
UK	44	40.1	48.1%	50.6%

† The national median age is the median age of the entire population. The median age of the population between 18 and 65 year-old is not available in all countries. Source: Eurostat (2018).

Table B2
Standard deviations of random parameter estimates of the MXL on hypothetical adoption in Table 3.[†]

	Pooled	DE	ES	FR	IT	PL	RO	SE	UK
subsidy	−0.407***	0.011***	−0.015***	−0.002	−0.009***	−0.003	−0.009***	−0.011***	−0.005
	(0.000)	(0.000)	(0.000)	(0.752)	(0.002)	(0.636)	(0.001)	(0.000)	(0.101)
savings	0.004***	0.231***	0.167***	0.195***	0.160***	0.188***	0.180***	0.215***	0.160***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
display	0.004	0.067	0.006	0.019	0.011	0.017	0.267*	−0.443***	−0.032
	(0.946)	(0.732)	(0.951)	(0.880)	(0.926)	(0.908)	(0.091)	(0.000)	(0.827)
remote	0.149***	0.492***	−0.016	−0.048	0.304**	0.630***	−0.408***	0.923***	0.249*
	(0.000)	(0.000)	(0.926)	(0.847)	(0.030)	(0.000)	(0.001)	(0.000)	(0.095)
rec_expert	−0.229***	−0.273	−0.481***	0.524***	−0.553***	−0.585***	−0.623***	0.361	0.351**
	(0.000)	(0.336)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.111)	(0.019)
rec_provider	−0.013	0.048	−0.022	−0.006	−0.050	−0.035	−0.093	−0.003	−0.013
	(0.849)	(0.739)	(0.875)	(0.978)	(0.820)	(0.859)	(0.756)	(0.990)	(0.908)
ASC	−7.208***	8.859***	9.833***	9.121***	6.316***	9.848***	6.172***	10.376***	10.179***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loglikelihood	−24,079.85	−2770.72	−3566.63	−2554.85	−2392.14	−2877.12	−2272.29	−2963.08	−3169.85
Number of observations	99,306	12,960	15,822	11,178	9828	12,780	10,278	13,068	13,392
Number of participants	5517	720	879	621	546	710	571	726	744

p-values in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
† The sign of the estimated standard deviation is irrelevant. Negative values should be interpreted as being positive

Table B3
Results of pooled MXL on hypothetical adoption including country interaction terms.

	FR(base)	Interaction terms with country dummies						
		DE	*ES*	*IT*	*PL*	*RO*	*SE*	*UK*
Means of parameter estimates								
price	−0.007***							
	(0.000)							
subsidy	0.349***	−0.004***	−0.003**	0.001	0.003**	0.004***	−0.001	−0.002
	(0.000)	(0.003)	(0.013)	(0.620)	(0.025)	(0.007)	(0.640)	(0.136)
savings	0.004***	0.050***	−0.026**	−0.041***	0.001	−0.027**	−0.008	−0.056***
	(0.001)	(0.000)	(0.024)	(0.001)	(0.949)	(0.027)	(0.485)	(0.000)
display	0.322***	0.112*	0.037	0.022	0.118*	0.178***	0.126*	0.053
	(0.000)	(0.097)	(0.545)	(0.750)	(0.072)	(0.009)	(0.055)	(0.410)
remote	0.211***	−0.028	0.187***	0.137**	0.321***	0.331***	0.260***	0.011
	(0.000)	(0.665)	(0.002)	(0.037)	(0.000)	(0.000)	(0.000)	(0.861)
rec_expert	0.310***	0.041	−0.018	0.072	−0.248***	0.256***	−0.120	−0.187**
	(0.000)	(0.655)	(0.835)	(0.441)	(0.005)	(0.005)	(0.175)	(0.033)
rec_provider	0.283***	−0.099	−0.019	0.079	−0.412***	0.281***	−0.205**	−0.103
	(0.000)	(0.262)	(0.813)	(0.375)	(0.000)	(0.001)	(0.016)	(0.218)
ASC	−5.650***	−0.432*	−2.592***	−1.187***	−1.119***	−3.677***	−1.189***	−1.077***
	(0.000)	(0.085)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Standard deviations of parameter estimates[†]								
subsidy	0.005***							
	(0.000)							
saving	0.152***							
	(0.000)							
display	−0.040							
	(0.575)							
remote	0.253***							
	(0.000)							
rec_expert	−0.396***							
	(0.000)							
rec_provider	0.013							
	(0.812)							
ASC	6.723***							
	(0.000)							
Loglikelihood	−23,703.75							
Number of observations	99,306							
Number of participants	5517							

p-values in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
† The sign of the estimated standard deviation is irrelevant. Negative values should be interpreted as being positive.

Table B4
Results of MXL model on hypothetical adoption including attitude interaction terms.

	Pooled	DE	ES	FR	IT	PL	RO	SE	UK
Means of parameter estimates									
price	−0.009***	−0.010***	−0.010***	−0.010***	−0.008***	−0.009***	−0.007***	−0.011***	−0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
subsidy	0.002***	0.332***	0.240***	0.108***	0.176***	0.261***	0.173***	0.261***	0.126***
	(0.000)	(0.000)	(0.000)	(0.009)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
savings	0.194***	−0.007***	−0.003*	0.001	0.004**	0.009***	0.008***	0.002	−0.000
	(0.000)	(0.001)	(0.092)	(0.591)	(0.032)	(0.000)	(0.000)	(0.362)	(0.827)
display	0.349***	0.657***	0.485***	0.450***	0.627***	0.147	0.941***	0.356***	0.212**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.172)	(0.000)	(0.003)	(0.028)
remote	0.352***	0.392***	0.448***	0.473***	0.522***	−0.199**	0.868***	0.063	0.256***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.036)	(0.000)	(0.579)	(0.003)
rec_expert	0.408***	0.540***	0.360***	0.276**	0.254**	0.305***	0.274**	0.418***	0.346***
	(0.000)	(0.000)	(0.000)	(0.031)	(0.014)	(0.007)	(0.020)	(0.006)	(0.001)
rec_provider	0.308***	0.233*	0.472***	−0.075	0.350***	0.679***	0.517***	0.555***	0.271**
	(0.000)	(0.099)	(0.000)	(0.590)	(0.003)	(0.000)	(0.000)	(0.002)	(0.018)
ASC	−1.906***	−1.840***	−2.846***	−1.619***	−2.259***	−2.251***	−1.004***	−2.266***	−2.886***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
hi_inno*savings	0.064***	0.073	0.062**	0.196***	0.080**	0.037	0.089***	0.018	0.069**
	(0.000)	(0.120)	(0.039)	(0.000)	(0.010)	(0.309)	(0.002)	(0.686)	(0.037)
hi_inno*_display	0.194***	−0.071	0.130	0.255	0.369***	0.244*	0.394**	0.259	0.243*
	(0.000)	(0.662)	(0.277)	(0.112)	(0.007)	(0.102)	(0.013)	(0.134)	(0.084)
hi_inno*remote	0.513***	0.606***	0.323***	0.827***	0.323**	0.669***	0.244*	0.853***	0.653***
	(0.000)	(0.000)	(0.007)	(0.000)	(0.024)	(0.000)	(0.092)	(0.000)	(0.000)
hi_priv*remote	−0.243***	−0.499***	0.063	−0.086	−0.015	−0.569***	0.135	−0.516***	−0.332**
	(0.000)	(0.002)	(0.597)	(0.570)	(0.918)	(0.001)	(0.359)	(0.010)	(0.013)
hi_env_id*savings	0.056***	0.113**	0.041	0.151***	0.011	0.066*	−0.016	0.125***	0.123***
	(0.000)	(0.015)	(0.197)	(0.002)	(0.735)	(0.072)	(0.558)	(0.004)	(0.000)
hi_env_id*display	0.064	−0.024	0.141	−0.219	0.049	0.278*	0.136	0.375**	0.053
	(0.146)	(0.878)	(0.273)	(0.168)	(0.718)	(0.061)	(0.394)	(0.031)	(0.705)
Standard deviations of parameter estimates†									
subsidy	0.024***	0.524***	0.353***	0.490***	0.284***	0.354***	0.242***	0.489***	0.362***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
savings	0.304***	−0.033***	−0.034***	0.026***	−0.027***	−0.027***	−0.024***	0.035***	0.027***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
display	0.810***	0.892***	0.751***	0.991***	0.785***	−0.902***	−0.828***	0.870***	0.907***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
remote	0.918***	−0.150	−0.384*	0.646***	−0.457**	0.597***	0.636***	1.137***	0.506***
	(0.000)	(0.545)	(0.064)	(0.001)	(0.021)	(0.002)	(0.001)	(0.000)	(0.005)
rec_expert	−0.718***	−1.108***	−0.759***	0.894***	−0.665***	0.849***	−1.077***	1.357***	1.042***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
rec_provider	0.411***	1.309***	0.937***	−0.918***	0.953***	1.369***	0.914***	1.896***	1.015***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Loglikelihood	−24,470.97	−2965.20	−3632.89	−2576.00	−2488.86	−2692.13	−2582.87	−3028.86	−3462.91
Number of observations	92,484	12,546	14,706	9990	9486	11,052	9576	12,276	12,852
Number of participants	5138	697	817	555	527	614	532	682	714

p-values in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
† The sign of the estimated standard deviation is irrelevant. Negative values should be interpreted as being positive.

Table B5
Results of MXL attitude-interaction model on hypothetical adoption including two-way interaction terms between country dummies and attributes and three-way interaction terms between country dummies, attributes and attitudes.

	FR(base)	Two- and three way interaction terms with country dummies						
		DE	*ES*	*IT*	*PL*	*RO*	*SE*	*UK*
Means of parameter estimates								
price	−0.007***							
	(0.000)							
subsidy	0.348***	−0.004***	−0.003**	0.001	0.003**	0.004***	−0.001	−0.002
	(0.000)	(0.003)	(0.016)	(0.566)	(0.021)	(0.005)	(0.681)	(0.144)
savings	0.003***	0.114***	0.033*	−0.004	0.047**	0.024	0.067*	−0.024
	(0.001)	(0.000)	(0.082)	(0.847)	(0.015)	(0.267)	(0.000)	(0.204)
display	0.326***	0.217**	0.133	−0.002	0.075	0.216*	0.204**	0.106
	(0.000)	(0.035)	(0.200)	(0.986)	(0.478)	(0.071)	(0.039)	(0.302)
remote	0.138***	0.176*	0.300***	0.240**	0.485**	0.439***	0.421***	0.138
	(0.000)	(0.098)	(0.003)	(0.029)	(0.000)	(0.000)	(0.000)	(0.182)
rec_expert	0.224***	0.044	−0.014	0.076	−0.251***	0.265***	−0.114	−0.186**
	(0.005)	(0.639)	(0.871)	(0.416)	(0.005)	(0.005)	(0.202)	(0.035)
rec_provider	0.094	−0.098	−0.021	0.077	−0.416***	0.297***	−0.208**	−0.105
	(0.241)	(0.269)	(0.797)	(0.395)	(0.000)	(0.001)	(0.015)	(0.215)
ASC	−5.037***	−0.484**	−2.586***	−1.184***	−1.051***	−1.424***	−1.278***	−1.211***
	(0.000)	(0.049)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
*hi_inno*savings*	0.062***	−0.090***	−0.075***	−0.026	−0.020	−0.015	−0.075***	−0.042*
	(0.001)	(0.000)	(0.001)	(0.319)	(0.419)	(0.566)	(0.002)	(0.083)
*hi_inno*_display*	0.113	−0.273**	−0.149	0.062	0.078	0.020	−0.203	−0.159
	(0.271)	(0.050)	(0.253)	(0.664)	(0.572)	(0.889)	(0.138)	(0.235)
*hi_inno*remote*	0.431***	−0.218*	−0.279**	−0.273**	−0.145	−0.390***	−0.115	−0.191
	(0.000)	(0.092)	(0.022)	(0.042)	(0.255)	(0.005)	(0.369)	(0.129)
*hi_priv*remote*	−0.087	−0.145	0.042	0.062	−0.243**	0.222*	−0.218*	−0.057
	(0.356)	(0.257)	(0.722)	(0.644)	(0.053)	(0.094)	(0.097)	(0.650)
*hi_env_id*savings*	0.074***	−0.020	−0.033	−0.050**	−0.070***	−0.090***	−0.068***	−0.005
	(0.000)	(0.417)	(0.153)	(0.049)	(0.004)	(0.000)	(0.006)	(0.836)
*hi_env_id*display*	0.038	0.082	−0.013	−0.030	−0.004	−0.107	0.084	0.090
	(0.708)	(0.557)	(0.922)	(0.831)	(0.977)	(0.454)	(0.544)	(0.504)
Standard deviations of parameter estimates[†]								
subsidy	0.006***							
	(0.000)							
saving	0.152***							
	(0.000)							
display	−0.038							
	(0.599)							
remote	0.226***							
	(0.000)							
rec_expert	0.398***							
	(0.000)							
rec_provider	−0.014							
	(0.797)							
ASC	6.344***							
	(0.000)							
Loglikelihood	−24,209.43							
Number of observations	92,414							
Number of participants	5138							

p-values in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.
† The sign of the estimated standard deviation is irrelevant. Negative values should be interpreted as being positive.

Table B6
Results of pooled Probit model on stated past adoption including country interaction terms (marginal effects).

	FR(base)	Interaction terms with country dummies						
		DE	*ES*	*IT*	*PL*	*RO*	*SE*	*UK*
hi_inno	0.065***	−0.063	−0.068	−0.500***	−0.436**	−0.309*	−0.505***	−0.039
	(0.000)	(0.754)	(0.694)	(0.007)	(0.017)	(0.094)	(0.008)	(0.825)
hi_priv	−0.010	−0.081	−0.024	0.194	0.029	0.027	0.053	−0.178
	(0.386)	(0.722)	(0.898)	(0.330)	(0.884)	(0.893)	(0.814)	(0.370)
hi_aut	−0.003	−0.210	−0.066	−0.476**	−0.027	−0.204	−0.358	−0.038
	(0.813)	(0.352)	(0.723)	(0.016)	(0.893)	(0.290)	(0.108)	(0.847)
hi_env_id	0.037***	0.131	0.159	0.316*	0.090	0.070	0.308	0.390**
	(0.001)	(0.506)	(0.359)	(0.089)	(0.622)	(0.706)	(0.102)	(0.028)
age	−0.002***							
	(0.000)							
low_inc	−0.062***							
	(0.000)							
hi_ed	0.019*							
	(0.092)							
familysize	0.003*							
	(0.097)							
urban	0.036***							
	(0.003)							
house	−0.006							
	(0.647)							
owner	0.092***							
	(0.000)							
DE	−0.069***							
	(0.001)							
ES	0.045*							
	(0.062)							
IT	0.106***							
	(0.000)							
PL	0.096***							
	(0.001)							
RO	0.141***							
	(0.000)							
SE	−0.047**							
	(0.034)							
UK	0.084***							
	(0.001)							
Loglikelihood	−2292.72							
N	5138							

p-values in parentheses.
* $p < 0.10$.
** $p < 0.05$.
*** $p < 0.01$.

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