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It's Cool! Analysis of Factors That Influence Smart Thermostat Adoption Intention

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Abstract Smart thermostats represent an innovative smart home technology and a growing commercial opportunity, yet little is known about the salient factors that affect the adoption of such devices. To address this gap in research, we conduct a three-stage study that progresses through belief elicitation, exploratory factor analysis and confirmatory factory analysis within a nomological network. We leverage the mixed methods approach to explore the factorial structure of salient perceived benefits and concerns associated with smart thermostats, and we examine the effects of the emergent factors on the adoption intention. We discover that a novel factor, which we term techno-coolness, is the key predictor of the smart thermostat adoption intention. Techno-coolness encompasses the perceptions that a smart thermostat can make a home look modern and futuristic, be fun to use, and make the user feel technologically advanced. We also find that compatibility concerns as well as privacy concerns are significant impediments to the smart thermostat adoption intention.

Keywords: smart home, technology adoption, mixed-methods research, smart thermostat, analysis of factors.

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1 Introduction

Continued advances in information and communication technologies have led to the continuous introduction of different types of smart home technologies (SHTs). SHTs span a very broad range of innovative products that can provide security and access controls, home healthcare, smart kitchen and home appliances, as well as self-learning heating and cooling systems, among others (Markets and Markets, 2017)(Markets and Markets, 2017). Industry estimates suggest that smart home technologies will represent a $137 billion market opportunity by 2023 (Markets and Markets, 2017). Despite the practical importance of this market, there has been relatively little academic research on the factors that influence SHT adoption.

Smart thermostats are an important type of device in the smart home ecosystem because they promise to simultaneously accomplish the dual goals of 1) improving the home experience through adaptive temperature regulation and 2) reducing energy expenditures through optimization of the home heating and cooling systems. The commercial market for smart thermostats is expected to reach $5.9 billion by 2020 (Markets and Markets, 2017)(Markets and Markets, 2015). Prior research on smart home technologies has been largely done outside of the United States and limited to the application of TAM and UTAUT theories (Park, Kim, Kim, & Kwon, 2018; Wang, McGill, & Klobas, 2018; Yang, Lee, & Zo, 2017). Little is known about the *salient* factors that affect the adoption of smart thermostats and similar technological artifacts. We begin to address this knowledge gap in this study. Responding to calls for context-specific theory development (Hong, Chan, Thong, Chasalow, & Dhillon, 2013), we conduct a three-stage study that progresses through elicitation of salient perceived benefits and concerns associated with smart thermostats, exploratory factor analysis (EFA) of the elicited perceived benefits and concerns, and confirmatory factor analysis (CFA) within a broader nomological network, wherein we evaluate the effects of the emergent constructs on the smart thermostat adoption intention.

We find that a new construct, which we term *techno-coolness*, is the key predictor of the smart thermostat adoption intention. *Techno-coolness* captures the perceptions that a smart thermostat can make a home look modern and futuristic, be fun to use, and make the user feel technologically advanced. We also find that security and privacy concerns, as well as concerns about the smart thermostat compatibility with the existing heating and cooling systems, are the salient factors that negatively affect smart thermostat adoption intention.

Our core theoretical contribution is the identification of t*echno-coolness* as the key predictor in the adoption of novel smart home technologies. *Techno-coolness* expands the list of technology-related constructs that need to be considered in the context of individual voluntary novel technology adoption and it complements the extant literature that highlights the utilitarian and hedonic motives in technology adoption (Venkatesh, Thong, & Xu, 2012). The key practical implication of our study is the importance of *techno-coolness* perceptions over the functional benefits in the adoption of smart home technologies. Smart home technologies that merely provide functional benefits may fail to win user acceptance if they do not enhance perceptions of *techno-coolness*.

2 Theoretical background

2.1 Smart home related research

A smart home is defined as "a residence equipped with computing and information technology which anticipates and responds to the needs of the occupants, working to promote their comfort, convenience, security, and entertainment through the management of technology within the home and connections to the world beyond" (Aldrich, 2003). Smart home technologies include sensors, monitors, interfaces, appliances, and other types of connected devices.

Much of the research on the adoption of SHTs has focused on the home healthcare applications for the elderly. A number of studies conducted focus groups and surveys with the elderly to assess the perceived benefits and concerns associated with in-home monitoring technologies: portable blood pressure monitors, fall sensors, cameras, etc. (Coughlin, D'Ambrosio, Reimer, & Pratt, 2007; Courtney, 2008; Demiris, Hensel, Skubic, & Rantz, 2008; Townsend, Knoefel, & Goubran, 2011). The consensus that emerges from these studies is that older adults generally view their homes as sanctuaries and they are concerned about the loss of autonomy that may result from the installation of monitoring technologies (Ziefle, Röcker, & Holzinger, 2011). Although the elderly appreciate the potential benefits offered by in-home monitoring technologies, they generally express concern over the loss of privacy associated with the monitoring technology use (Liu, Stroulia, Nikolaidis, Miguel-Cruz, & Rincon, 2016).

In a parallel stream of research, smart energy meters that can support centralized energy distribution control and help alleviate the electric grid load during peak times have received attention in electrical engineering and energy policy research (Arif et al., 2013; Palensky & Dietrich, 2011). A recent survey of UK residents revealed that energy savings and added convenience were the highest rated benefits expected from SHTs (Wilson, Hargreaves, & Hauxwell-Baldwin, 2017). However, the survey also showed that residents are wary of overreliance on technology.

Security and privacy concerns have been repeatedly raised in relation to smart meter adoption (Efthymiou & Kalogridis, 2010; Sankar, Rajagopalan, & Mohajer, 2013). An engineering analysis of smart meters substantiated the legitimacy of privacy concerns. The analysis of encrypted information transmission patterns from smart meters showed that it is possible to infer appliance usage patterns even without knowing the content of the communications (McKenna, Richardson, & Thomson, 2012).

In summary, some of the prior research on SHTs has been narrowly focused on in-home monitoring devices for the elderly and electric smart meters. The common observations across these contexts suggest that SHT adoption involves weighing perceived functional benefits against the potential loss of privacy and possibly a sense of autonomy. In the next section, we review the key research studies on technology adoption across a broader set of contexts.

2.2 Technology adoption

Factors influencing technology adoption are a central theme in Information Systems research (Venkatesh et al., 2012; Venkatesh, Thong, & Xu, 2016). The Technology Acceptance Model (TAM) laid the foundation for much of the research in this domain (Davis, 1989). TAM draws on the theory of reasoned action (TRA) (Fishbein, 1979) and it posits that technology performance expectancy (perceived usefulness) and perceived effort expectancy (perceived ease of use) are the key determinants that influence the technology adoption intention.

Although TAM and UTAUT have proven their value across different technology adoption domains (Venkatesh, Bala, & Sambamurthy, 2016), a number of studies have demonstrated that alternative theoretic perspectives are better at uncovering the key factors that influence technology acceptance in specific contexts. For example, Hsiao (2003) showed that *fear* and *distrust* were the key factors that helped explain the adoption intention in an e-marketplace. Brown and Venkatesh (2005) found that *perceived usefulness for others* (children) had a significant effect on home computer adoption. Baird et al. (2012) demonstrated that a complex set of *contingencies* influenced the adoption of electronic patient portals by healthcare providers. In summary, although TAM and its successor, UTAUT, offer general frameworks encompassing factors that can influence the technology adoption intention, research within specific contexts has found that context-specific factors afford a better, more contextualized understanding of the phenomenological drivers in the respective contexts.

3 Methodology

Following the calls for context-focused research in information systems (Hong et al., 2013) and in recognition of the novelty of smart home technologies that may pose challenges for generic theoretical models being able to capture the key contextual factors that influence technology adoption in this domain, we draw on theory of reasoned action as the overarching theoretical framework and we conduct a three-stage study. Our analysis proceeds through three stages: Stage 1- elicitation of salient perceived benefits and concerns associated with smart thermostats, Stage 2 - exploratory factor analysis, and Stage 3 – confirmatory factor and nomological network analysis.

For each stage in the study, we recruited a new set of participants using Amazon's Mechanical Turk (AMT). AMT is an online labor market for micro tasks that has received support as a valuable source of research participants across disciplines (Buhrmester, Kwang, & Gosling, 2011; Feild, Jones, & Miller, 2010; Holden, Dennie, & Hicks, 2013; Kittur, Chi, & Suh, 2008; Lowry, D'Arcy, Hammer, & Moody, 2016). To avoid potential cross-cultural effects, we limited the participation to AMT "workers" from the United States. We relied on Qualtrics, a commercial survey platform, to capture the participants' responses to our surveys in each stage of the study.

For Stage 1, we recruited 24 participants from AMT. We collected basic participants' demographic data and we asked the participants to indicate ownership of different smart home technologies. None of the participants in this stage indicated ownership of a smart thermostat. We exposed the participants to a 5-minute video describing smart thermostats. We then asked the participants to share their opinion on the top 5 potential benefits and top 5 concerns associated with smart thermostats. Based on the content analysis of the themes that emerged in Stage 1, we generated items that reflect frequently mentioned perceived benefits and concerns.

In Stage 2, we recruited a new group of 150 participants from AMT. We collected their basic demographic information and we exposed the participants to the same video describing smart thermostats. We then asked the participants to indicate their agreement or disagreement with the items that were generated in Stage 1. We used 7-point Likert scales anchored in "1 – Strongly agree" and "7 – Strongly disagree". We performed exploratory factor analysis using SPSS version 25 using oblimin factor rotation to account for potential correlation among the emergent constructs. In Stage 2, we inductively developed a list of latent constructs that captured the themes that emerged from the analysis.

In Stage 3, we recruited a new group of 625 participants from AMT. We collected their basic demographic information and we exposed the participants to the video describing smart thermostats. We surveyed the participants on the constructs that emerged in Stage 2. We measured their adoption intention using the established scale from UTAUT2 (Venkatesh et al., 2012).

4 Results

4.1 Stage 1 – Perceived benefits and concerns elicitation

Based on the elicited perceived benefits and concerns, we developed a list of 68 items that reflect commonly stated perceived benefits and concerns. The items included such statements as "A smart thermostat will help me save money on electricity," "A smart thermostat will make my home more modern," and "A smart thermostat can be hacked."

4.2 Stage 2 – Exploratory factor analysis

We conducted an exploratory factor analysis following the recommendations of Treiblmaier & Filzmoser (2010). We performed principal axis factor analysis with oblique rotation using SPSS version 25. We chose to use the oblique rotation to allow for potential correlations among the latent constructs reflected in the responses to individual survey items. We relied on two criteria to determine the number of factors to retain. First, we examined the scree plot. Second, we performed parallel analysis by comparing individual factor eigenvalues against a set of simulated eigenvalues given the parameters in our study (Hayton, Allen, & Scarpello, 2004). This approach has been shown to avoid potential under and over factor specification in EFA.

The exploratory factor analysis is an established methodology for "identifying the underlying dimensions of a domain of functioning" in management, marketing, psychology, and information systems research (Fabrigar, Wegener, MacCallum, & Strahan, 1999; Hurley, Scandura, Schriesheim, & Brannick, 1997; Mamonov & Benbunan-Fich, 2017; Stewart, 1981). Following the recommendations of Fabrigar et al., (1999), we examined the content of individual constructs to develop a theoretical foundation for the latent factors that can affect the adoption of smart thermostats.

Due to manuscript length constraits, we present a very abbreviated summary of the exploratory factor analysis here. We found several well established factors (performance expectancy, effort expectancy, information privacy and security concerns and cost concerns), as well as more context-specific factors (installation, fragility and compatibility concerns) in our analysis. We also uncovered a novel factor that captures beliefs related to potential of smart thermostats to make the users feel "technologically advanced" and "up to date" while also making the homes feel more modern and futuristic. Such potential effects of technology have been discussed in individual psychology literature that focused on what makes some consumer products *cool* (Bruun, Raptis, Kjeldskov, & Skov, 2016; Culén & Gasparini, 2012). Following this stream of research, we term the factor *techno-coolness*.

Item analysis of the *techno-coolness* factor suggests that it captures a complex set of benefits that the technology users expect to derive through the product use. On the one hand, adoption of the technology promises to transform the esthetic appearance of one's home by making it "more modern" and "technologically advanced". On the other, the potential adopters expect to derive personal image benefits ("A smart thermostat in my home would make me feel like I was making the most out of newer technology") and experience joy while using it. The emergent complex structure of techno-coolness is consistent with prior conceptions of *cool* products that are expected to serve a broad spectrum of individual goals, including self-presentation, mastery, fun, and innovativeness (Culén & Gasparini, 2012).

Stage 3 – Confirmatory factor and nomological network analysis

In the third stage we recruited 625 new participants from AMT. Thirteen responses were excluded because the participants failed to answer the attention control questions correctly or there was evidence of a common response bias, leaving us with a sample of 612 usable responses.

Following the recommendations of Gefen et al. (2011) on theory development, we relied on PLS for data analysis using SmartPLS version 3 software. PLS analytical method relies on iterative estimation of item loadings on the latent factors and the correlations between the latent factors. Our presentation of the results follows the latest recommendations on PLS reporting in Hair Jr et al. (2016).

In the first step of the analysis, we assessed the discriminant validity of the measurement model. All items had loadings above 0.7 on the respective constructs and below 0.5 on all other constructs indicating good discriminant validity. We are not showing the item loadings here due to the manuscript length constraints. Next, we evaluated measurement reliability. Cronbach's alphas are above 0.87, rho values are above 0.7 and composite reliability scores are above 0.85 for all scales in our instrument indicating good measurement reliability. Average variance extracted (AVE) is above 0.7 and the square root of AVE is higher than any inter-construct correlation. Table 1 summarizes the reliability and discriminant analysis results.

Table 1: Measurement reliability and discriminant validity analysis

	CA	RH	CR	AI	CC	CO	EE	PE	IC	PC	RC	TC
Adoption Intention (AI)	0.97	0.97	0.97	0.96								
Compatibility concerns (CC)	0.90	0.92	0.91	-0.33	0.87							
Cost concerns (CO)	0.93	0.98	0.93	-0.31	0.36	0.89						
Effort Expectancy (EE)	0.87	0.90	0.85	-0.25	0.39	0.19	0.72					
Performance expectancy (PE)	0.97	0.97	0.97	0.43	-0.19	-0.20	-0.12	0.94				
Installation concerns (IC)	0.96	0.99	0.96	-0.18	0.44	0.30	0.51	-0.10	0.93			
Privacy concerns (PC)	0.98	0.98	0.97	-0.26	0.24	0.17	0.15	-0.07	0.17	0.87		
Reliability concerns (RC)	0.90	0.92	0.91	-0.33	0.27	0.32	0.39	-0.21	0.42	0.28	0.88	
Techno-coolness (TC)	0.92	0.93	0.92	0.55	-0.07	-0.21	-0.09	0.56	-0.01	-0.13	-0.22	0.79

CA – Cronbach's alpha, RH – rho, CR – composite reliability, average variance extracted (AVE) is shown in the diagonal.

In the next step, we examined the relationships between the constructs that represent different smart thermostat related perceived benefits/concerns and the adoption intention by running the bootstrapping procedure. We found that *performance expectancy* ($\beta = 0.14$, $p<0.05$) and techno-coolness ($\beta = 0.36$, $p<0.001$) are positively correlated with the adoption intention, whereas *compatibility concerns* ($\beta = -0.17$, $p<0.01$) and *privacy concerns* ($\beta = -0.12$, $p<0.05$) are negatively correlated with the adoption intention indicating that these factors have negative effects on the adoption intention. *Effort expectancy*, *installation concerns*, *reliability concerns* and *cost concerns* are not significantly correlated with the adoption intention. Among the control variables, only income is statistically significantly negatively correlated with the adoption intention ($\beta = -0.20$, $p<0.01$). The results are summarized in Figure 1.

5 Discussion

In this study, we sought to uncover salient user beliefs that can affect the adoption of smart thermostats as an example of a commercially important smart home technology. Through progressive steps of belief elicitation, exploratory and confirmatory factor analysis, and nomological network analysis, we uncovered eight

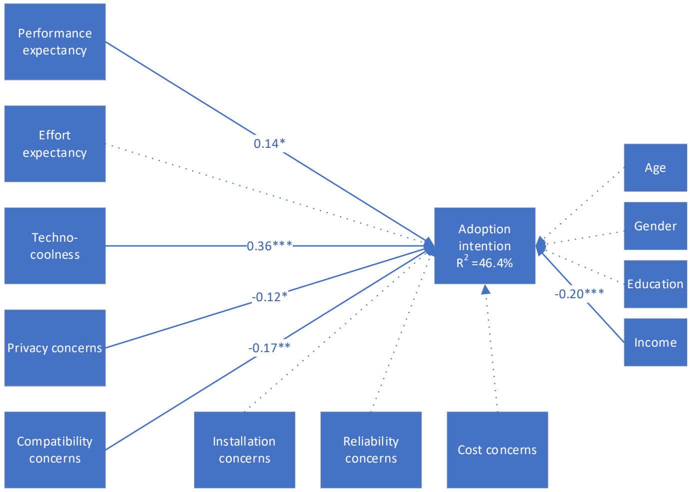

Figure 1: Structural model analysis

salient factors that may affect smart thermostat adoption intention. Among the eight factors, *performance expectancy* and *privacy concerns* are two well-known factors in technology adoption research (Venkatesh, Thong, et al., 2016) We found that *performance expectancy* and *privacy concerns* have countervailing effects on the smart thermostat adoption intention, though these effects are relatively minor. *Performance expectancy's* effect size is 0.02 and *privacy concerns'* effect size is 0.024. We discovered that a novel factor, which we termed *techno-coolness*, has the largest effect size on the smart thermostat adoption intention (f^2 =0.164). We also found that *compatibility concerns* had the second largest effect size of 0.036. While the users shared a number of additional concerns during the elicitation stage of our study: *effort expectancy*, *installation concerns*, *reliability concerns*, and *cost concerns*, these concerns did not have a statistically significant effect on the adoption intention in our nomological network when we surveyed a broader sample in stage 3 of our study. Overall, the factors in our model explain 46.4% of variance in the adoption intention, suggesting that we captured the core factors that influence the adoption intention in this context.

Our study makes a number of contributions to theory. First, we uncover *techno-coolness* as a novel construct that can significantly affect the adoption of innovative technologies. *Techno-coolness* is a multi-dimensional construct. It captures the technology capacity to 1) make the person feel more technologically savvy, 2) make the person and/or the person's environment "look good" and appear more modern, and 3) be fun to use. The complex dimensionality of *techno-coolness* likely emerges from the complex motives that underlie the consideration of adopting innovative smart home technologies. Studies on general product *coolness* suggest that *cool* products satisfy a complex set of individual goals that may include accomplishment, connection with others, identification development and sensory experiences (Holtzblatt, 2011). The complex dimensionality of *techno-coolness* is also consistent with prior attempts to develop general measures for *cool* consumer products that noted that general *coolness* may be reflected in product attributes (original, fresh, unique, distinct, hip), the subculture associated with the product use (unique and different), and product utility (Sundar, Tamul, & Wu, 2014). At the same time, *techno-coolness* is clearly distinct from general product *coolness* in that it captures the association between technology that is being perceived as innovative/modern/futuristic and the expected personal image and utility benefits associated with the innovative technology use. Marketing research has noted that some retro consumer products can be *cool* (Culén & Gasparini, 2012). It is unlikely that older technology can be perceived as *techno-cool.*

Our second theoretical contribution is the development of context-specific factors that may affect smart thermostat adoption. In addition to *techno-coolness* being the most significant factor in our model, the second most important factor is *compatibility concerns*. *Compatibility concerns* have been noted as an important consideration in technology adoption in the past (Agarwal & Prasad, 1998; Cooper & Zmud, 1990), but they are infrequently considered in the more recent research (Venkatesh, Thong, et al., 2016). Successful smart thermostat adoption requires interoperability with the existing heating and cooling systems. Our results reveal an important consideration that likely affects many other smart home technologies.

Our study also has a number of implications for practice. First, the results of our study suggest that functional benefits afforded by smart home technologies may not be the key reason why people would consider buying them. *Techno-coolness* is the key factor that affects the smart thermostat adoption intention in our study. Therefore, consideration of *techno-coolness* has to be an essential step in smart home technology development. If it is not *techno-cool*, it may be not be adopted. The second insight for practice emerges from the fact that our elicitation of concerns associated with smart thermostat adoption produced a range of concerns including general effort expectancy in learning how to operate the device, installation and reliability concerns, and concerns about the high cost of technology. Rather surprising, we found that most of the concerns had no effect on the smart thermostat adoption intention. These results suggest that even though users may voice many concerns in product evaluation, these concerns may not affect their adoption intention.

Lastly, we should note that no research is without limitation and our study is not an exception. While we sought to recruit a diverse group of participants for all stages of our study, the AMT subject pool may not represent the larger population, and further research would be required to confirm the applicability of the results in our study within the broader population. Further, we limited the participation in our study to only AMT subjects based in the United States. It is likely that the cultural context will be an important factor on the consideration of smart home technology adoption in different countries. Further research would be required to explore the cultural factors that may play a role in smart home technology adoption.

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