# HOME, SWEET HOME: HOW WELL-BEING SHAPES THE ADOPTION OF ARTIFICIAL INTELLIGENCE-POWERED APARTMENTS IN SMART CITIES

Lars Meyer-Waarden, Julien Cloarec, Carolin Adams, Dorothea Nilusha Aliman, Virginie Wirth

ESKA | « Systèmes d'information & management »

2021/4 Volume 26 | pages 55 à 88

ISSN 1260-4984
ISBN 9782747232944
DOI 10.3917/sim.214.0055

# Home, sweet home: How well-being shapes the adoption of artificial intelligence-powered apartments in smart cities

*Lars Meyer-Waarden*[*], *Julien Cloarec*[**], *Carolin Adams*[***], *Dorothea Nilusha Aliman*[****] & *Virginie Wirth*[*****]

[*]TSM Research, Université Toulouse Capitole, CNRS, Toulouse, France & Business Science Institute Luxembourg
[**]iaelyon School of Management, Université Jean Moulin Lyon 3, Magellan, Lyon, France
[***]tribe29 GmbH, Munich, Germany
[****]Chair for Marketing & Media, Westfälische Wilhelms-University, Münster, Germany
[*****]Osnabrück University, Osnabrück, Germany

## ABSTRACT

*The recent increase in the use of artificial intelligence (AI) and the Internet of Things has given rise to fundamental changes that affect users' daily lives. Smart connected objects and smart homes have appeared. The purpose of this study is to understand the acceptance and resistance factors of AI-based smart homes by combining the unified theory of acceptance and use of technology (UTAUT) with other relevant theories (technology acceptance theories from AI and robots research; regulatory focus theory; uses and gratifications theory; technology readiness theory) in a unified model. Cross-cultural data are collected in Western countries (France, Germany) and an Eastern country (China) and analyzed using ordinary least squares path analysis modeling. The results show that consumers pursue complementary types of goals when making decisions (e.g., utilitarian, prevention-oriented goals and affective, promotion-oriented goals involving well-being). We found a strong positive impact of smart homes' technology security, trust, and well-being on people's intention to use. Perceived privacy risks negatively influence people's intention to use only in developed countries.*

***Keywords:*** *smart home, smart city, artificial intelligence, IoT, technology acceptance, regulatory focus theory, uses and gratifications theory, technology trust, privacy concerns, well-being*

## RÉSUMÉ

*L'augmentation récente de l'utilisation de l'intelligence artificielle (IA) et de l'Internet des objets a donné lieu à des changements fondamentaux qui affectent la vie quotidienne des utilisateurs. Des objets connectés intelligents et des maisons intelligentes sont apparus. L'objectif de cette étude est de comprendre les facteurs d'acceptation et de résistance des maisons intelligentes basées sur l'IA en combinant la théorie unifiée de l'acceptation et de l'utilisation de la*


https://doi.org/10.54695/sim.026.04.055088

*technologie (UTAUT) avec d'autres théories pertinentes (théories d'acceptation de la technologie issues de la recherche sur l'IA et les robots ; théorie des focus régulateurs ; théorie des usages et gratifications ; théorie de la réceptivité à la technologie) dans un modèle unifié. Des données interculturelles sont collectées dans des pays occidentaux (France, Allemagne) et dans un pays oriental (Chine) et analysées à l'aide d'un modèle d'analyse de chemin des moindres carrés ordinaires. Les résultats montrent que les consommateurs poursuivent des types de buts complémentaires lorsqu'ils prennent des décisions (par exemple, des buts utilitaires, orientés vers la prévention, et des buts affectifs, orientés vers la promotion et impliquant le bien-être). Nous avons trouvé un fort impact positif de la sécurité technologique, de la confiance et du bien-être des maisons intelligentes sur l'intention d'utilisation. Les risques perçus en matière de vie privée n'influencent négativement l'intention d'utilisation que dans les pays développés.*

***Mots-clés :*** *maison intelligente, ville intelligente, intelligence artificielle, IoT, acceptation de la technologie, confiance technologique, vie privée, bien-être*

## 1. INTRODUCTION

The smart city concept emerged as a combination of "ideas about how information and communication technologies, mainly based on the Internet of the things (IoT), might improve the functioning of cities" (Batty *et al.*, 2012). The term smart city is thus gaining popularity, and every day, more cities are labeled smart; for example, in Bangkok, a full district was destroyed to create a new smart city, called One Bangkok, with smart buildings and smart apartments as well as roads and means of transport (Bangkok Post, 2021). Today, smart cities have become a major environmental, policy, and business challenge, as almost 55% of the world's population live in urban areas, and it is expected that the number will increase up to 66% by 2030 (United Nations, 2016). On the other hand, the concept of smart cities and what they include are still considered to be a work-in-progress (Camero & Alba, 2019), and academic research is scarce.

Smart homes, AI, and the IoT have been widely seen as promising to enhance the quality of life and well-being by providing personalized services and experiences (McKinsey Global Institute, 2013). The global smart home market is expected to grow by 25% per year to USD 119.26 billion by 2022 (Mordor Intelligence, 2021), while the European smart home market is expected to grow from USD 22.8 billion in 2018 to USD 44.0 billion by 2024 (Markets and Markets, 2020). Despite the potential benefits of smart homes and even if AI-based smart home technologies appear to be increasingly present in households, many consumers are still reluctant to use these technologies. The adoption and diffusion rate remains low (Yang *et al.*, 2017); household penetration was 7.5% in 2017 (Statista, 2021), and only 23% of European and U.S. consumers have high purchase or rental intentions (IoT World Today, 2019) because they do not want to partially or fully delegate decision-making authority to AI and machines. Their concerns include loss of control, loss of freedom, privacy issues, hacking, uncertainty, distrust, and fear that technology could harm their health (Balta-Ozkan *et al.*, 2014). Even if the academic community has intensified its efforts in examining the concepts of smart cities and homes, the perceptions of consumers about smart homes and the motives for adopting these solutions remain unclear (Marikyan *et al.*, 2019). It is therefore important to examine smart home acceptance and adoption and the users' perspective on the barriers that may hinder the implementation of smart homes. Based on these gaps coming from the literature review and future research recommendations, our study is conducted in France, Germany and China and contributes at both the theoretical and managerial levels to existing research in different ways: foremost, like most of the research in the domain of AI, the IoT comes from engineering and computer science rather than the management literature, our study offers different main contributions to management science research, shedding light on the research question, "which cognitive and affective factors positively and negatively influence the adoption of AI-based smart homes?"

On a theoretical level, our study thus contributes to information systems (IS) and marketing research and sheds light on consumers' perceptions about the risks and benefits of AI-based smart homes. To fill this void, we have tested a conceptually integrated model incorporating a unified theory of acceptance and use of technology (UTAUT; Venkatesh *et al.*, 2012) and other AI-based technology acceptance theories (Ostrom *et al.*, 2019; Wirtz *et al.*, 2018), regulatory focus theory (Higgins, 1997), uses and gratifications theory (Katz *et al.*, 1973) and technology readiness theory (Parasuraman & Colby, 2015) with less or no investigated affective variables as consumers pursue complementary types of goals when making decisions (e.g., utilitarian, prevention-oriented goals and affective, promotion-oriented goals, involving affection, happiness, and well-being) (Avnet & Higgins, 2006). We thus combine a part of the UTAUT (effort-and performance expectancy, with behavioral intention to use) with the AI-acceptance model from Ostrom *et al.* (2019) and the service robot acceptance model-sRAM (Wirtz *et al.*, 2018) taking into account variables such as technology trust, technology security (perceived by approximately 50% as main barriers according to a study of Statista (2021)), along with resistance factors such as privacy concerns (Pavlou, 2003), as there is scant research investigating customer resistance to technological innovations (e.g., Laukkanen, 2016). Next, we integrate trust into technology and well-being benefits, which are also highly relevant according to the study of Statista (2021). It is interesting to note that environmental benefits are not even cited by potential users. Therefore, instead of concentrating on the environmental benefits of smart homes, as in most existing studies in the literature (Balta-Ozkan *et al.*, 2014), we focus on well-being-oriented smart homes, which are emphasized as highly relevant by almost 60% of the potential users in the Statista study and are considered a research priority in IS and marketing research (Blut *et al.*, 2021). Furthermore, our research contributes to cross-cultural theory and understanding in IS research (Blut *et al.*, 2021). As most empirical studies about the effects of motivations of smart home use have focused only on a single country, we have addressed this gap by collecting data from diverse countries (China, France, Germany) that vary in terms of network/technology readiness (Parasuraman & Colby, 2015), cultures, uncertainty avoidance or risk aversions of privacy and technology risks (Hofstede, 1993).

## 2. LITERATURE REVIEW

Various definitions have been used to conceptualize and define smart cities, but no clear definition has been given. Through the IoT, the physical infrastructure, IT infrastructure, social infrastructure, and business infrastructure are connected to leverage the collective intelligence of the city. In smart city technologies, such as ICT, logistics, energy production, and IoT, applications are coordinated to create benefits for citizens in terms of well-being, inclusion and participation, environmental quality, and intelligent development (Attour *et al.*, 2020). Research on smart cities is done in the following domains: economy (e-commerce, e-business), mobility (public transport, logistics), governance (democratic process), people (work at home, education), living (smart homes for user well-being), and environment (energy, pollution) (Caragliu *et al.*, 2011). In the literature review, we see that most research has been done in the domain of smart economy, mobility, governance, people, living, and environment. Eighty percent of the existing publications are done in IT, CS, engineering, and urban studies research. Most publications have a strong technological focus with enabling technologies, such as the Internet of Things and Big Data and (mobile) network structure. Only 4% of the research is done in business and economics (Camero & Alba, 2019). China and the USA represent more than 30% of the research done, whereas France produces only 6% of the research about smart cities (Camero & Alba, 2019). Finally, most of the research has been done about smart environment (energy, pollution) and smart mobility (public transport, logistics) applications, while smart governance, smart people, smart economy, and smart living (smart homes and user adoption, usage, and experience) are relegated to a secondary place and lack adequate investigation, even though they have paramount importance. Furthermore, research from Europe and cross-country comparisons with emerging countries, such as China (Camero & Alba, 2019), is missing.

This brings us to the domain of smart living with the concept of the smart home: Balta-Ozkan *et al.* (2014, p. 66) define the smart home as "a residence equipped with a high-tech network, linking sensors and domestic devices, appliances, and features that can be remotely monitored, accessed or controlled, and provide services that respond to the needs of its inhabitants to promote their comfort, convenience, security, and entertainment". With the IoT, a smart home connects AI, digital technologies, sensors, captors, household electrical appliances, information and remote communication devices such as smartphones, and AI to enable remote automation and to control the home environment in terms of secured access, temperature, and lighting. Smart home objects are part of the smart home and replace existing products (e.g., connected windows or taps) or come in addition to existing ones (e.g., sensors). Examples include self-learning thermostats and security systems, smart water and energy controllers, connected body fat bathroom scales, and smart speakers; these products aim to achieve comfort, convenience, safety, health, a reduction in or automation of household labor, and energy efficiency to improve the users' overall well-being (Schill *et al.*, 2019). The smart home not only executes tasks explicitly assigned by the user but also actively collects and analyzes real-time big data from the environment and uses AI to propose suitable solutions for residents' comfort (Wu *et al.*, 2007). The AI service operates by self-understanding residents' behaviors to optimize or automate decision-making and achieve remote controllability (Ghayvat *et al.*, 2015). Automation means "the execution by a machine agent (usually a computer) of a function that was previously carried out by humans" (Parasuraman & Riley, 1997). Smart homes can be classified into three main types (De Silva *et al.*, 2012). The first category of smart homes assists occupants by recognizing their actions. This type of smart home promotes the well-being of occupants by providing information on users' safety and health care for the aging population or children's care. Well-being-related benefits refer to health-related and lifestyle services of comfort that can be achieved when the smart home manages the services of comfort (heating, air conditioning, air quality), chronic diseases, physical activity, and consultancy through doctors or coaches (Chan *et al.*, 2008). Furthermore, smart homes can improve socialization by increasing social capital and helping users to overcome the feeling of isolation (Percival & Hanson, 2006) through the implementation of services related to social support and assistance. The enabling power of smart home technology to assist and support people in their everyday activities affects self-perception in terms of self-esteem, adaptability, and competence. The second type of smart home is the surveillance home, which aims to process data to forecast and alert residents in case of upcoming disasters or security interventions (De Silva *et al.*, 2012). The third type of smart home is an ecological smart home that promotes environmental sustainability by enabling residents to monitor, control, and reduce their energy consumption (Balta-Ozkan *et al.*, 2014; Bhati *et al.*, 2017). The financial benefits of smart homes are typically associated with these environmental benefits.

A systematic review of the smart home literature confirms that a large majority of articles about smart homes were published in medical, aging, and technical or engineering journals (Marikyan *et al.*, 2019). We enhanced their literature review with the Web of Science by combining keywords such as “smart home,” “smart device,” “intelligent home,” “digital home,” “AI-based home,” and “smart home device.” We found in the period from 2010 to 2021 a total of 270 papers in peer-reviewed academic journals. The majority of these studies contextualize their approach toward a specific technological domain: the primary domains of investigation are home automation (128 articles) and IoT (62 articles) published mainly in computer or engineering journals (for example, IEEE Transactions on Consumer Electronics) with the scope encompassing engineering and research aspects of the design, construction, manufacture of smart home electronics, systems, software and services for consumers. A major part of the articles thus focuses on technology applications (mainly assistive) or single devices inside a smart home. Only 80 articles are published in business science journals focusing mainly on conceptual research without any empirical investigation with themes about technological challenges of IoT and smart technologies in general (i.e., smart grids, smart wearables). Furthermore, the management science literature predominantly focuses on the technical characteristics of smart homes and individual standalone smart devices (e.g., Toschi *et al.*, 2017), rather than fully connected smart homes with different devices. The focus on a single device does not give an adequate picture of the full range of medical, health, environmental, hedonic, utilitarian benefits of smart homes and the interoperability and multifunctionality of devices (e.g., Ehrenhard *et al.*, 2014). Furthermore, there is a gap in the research about the acceptance, adoption, and usage of smart homes from the end-users perspective. A few studies concentrate on the users’ perspectives of aging populations and medical points of view (e.g., Harris & Hunter, 2016), thus overlooking younger more promising user segments. Regarding the methodologies, most investigations used qualitative methodologies (Balta-Ozkan *et al.*, 2014) and less quantitative methodologies (Hubert *et al.*, 2019; Schill *et al.*, 2019). Finally, we narrowed the analyses to the following keywords: “smart home,” “smart device,” “intelligent home,” “digital home,” “AI-based home,” and “smart home device” combined with technology acceptance, namely, “TAM,” “UTAUT,” “Theory of reasoned action," "Theory of planned behavior," and "Adoption of smart homes." We found only ten studies (Table 1) focusing on the adoption and usage of smart homes from the end-users perspective (Aldossari & Sidorova, 2020; Bao *et al.*, 2014; Hubert *et al.*, 2019; Kim *et al.*, 2017; Klobas *et al.*, 2019; Park *et al.*, 2017; Schill *et al.*, 2019; Wang *et al.*, 2020; Yang *et al.*, 2017, 2018). Beyond that, most of these studies have methodological flaws, as they do not use scenarios or only employ descriptive verbal scenarios (and not vivid videos or virtual reality to simulate the smart home environment and its benefits) to frame a still picture for most users of this unfamiliar technology. This might make it hard to understand their functions and benefits.

**Table 1: Studies about smart home adoption**

| Authors | Theory | Country | Indep. Var. | Dep. Var. | N/Repr. | Survey/ Analyses Method |
|---|---|---|---|---|---|---|
| Bao *et al.* (2014) | TAM | China | PU, PEU, social recognition, secure home environment, technology risk, compatibility, cost | BIU | 310/NR/ Scenario | Verbal description SH SEM |
| Kim *et al.* (2017) | TAM, UTAUT | US | PU, PEU, Attitudes privacy risk, perceived fees, facilitating conditions, enjoyment, innovation resistance, Technicality | BIU | 269/NR | Scenario video SH Smart PLS |
| Park *et al.* (2017) | TAM | Korea | PU, PEU, enjoyment, connectedness, perceived behavioral control, compatibility, cost | BIU/ Attitudes | 1057/NR | Scenario verbal description SH SEM |
| Yang *et al.* (2017) | TPB, TAM | Korea | Subjective norms, behavioral control, automation, mobility, interoperability, security, privacy risk, physical risk, trust | Attitudes BIU | 216/NR | Scenario verbal description SH Smart PLS |
| Yang *et al.* (2018) | TAM | Korea | perceived control, automation, interconnectedness, reliability | BIU | 216/NR | Scenario verbal description SH SEM |
| Klobas *et al.* (2019) | TRA | US | Attitudes, control, security risk, age, education | Attitudes | 405/R | Scenario verbal description SH SEM |
| Hubert *et al.* (2019) | TAM, Innov. diffusion theory | Germany | PU, PEU, security risk, performance risk, time risk compatibility, result demonstrability, visibility | BIU | 409/NR/ | Scenario verbal description SH SEM |

| | | | | | | |
|---|---|---|---|---|---|---|
| Schill *et al.* (2019) | TPB, TAM | | PU, environmental concerns, happiness | BIU | 641/NR | NA<br>SEM |
| Aldossari & Sidorova (2020) | TAM, UTAU 2 | US | performance expectancy, effort expectancy, facilitating conditions, social influence, hedonic motivation, price value, trust, security risk, trust | Attitudes BIU | 343/NR/ | Scenario video SH<br>Smart PLS |
| Wang *et al.* (2020) | UTAUT | US | PE, EE, compatibility, social image, compatibility, privacy risk, performance risk, time risk, security risk, financial risk | BIU | 351/NR/ | Scenario verbal description SH<br>Smart PLS |

TPB: Theory of planned behavior, TRA: Theory of reasoned action, TAM: Technology acceptance model, UTAUT: Unified theory of acceptance and use of technology; PU: perceived usefulness; PEU: perceived ease of use; EE: Effort Expectancy, PE: Performance Expectancy, BIU: Behavioral Intention of Use.
NR: nonrepresentative sample.

In summary, the research literature shows that understanding "how and why users accept or reject AI-based smart homes" is an important issue, according to numerous calls for research about AI and smart environments (Foroudi *et al.*, 2018). Therefore, it is important to understand consumer attitudes toward and perceptions of these new technologies (Blut *et al.*, 2021). Furthermore, according to the study of Statista (2021), environmental benefits are not even cited by potential users. Academic research (Blut *et al.*, 2021) confirms this finding, showing that smart homes' perceived value comes mainly from utilitarian, social, health, and well-being benefits (environmental benefits are not found). Therefore, it makes more sense to work on smart home types that promote the well-being of occupants (e.g., health-related, sport, and lifestyle services of comfort) rather than on smart homes promoting environmental sustainability (De Silva *et al.*, 2012). Furthermore, environmental benefits are implicitly included, as the financial benefits of smart homes are typically associated with them (Statista, 2021). Our research thus shifts from a technology-driven research paradigm to a consumer-centric paradigm (Marikyan *et al.*, 2019) to explore the potential development of personalized user services to satisfy broader target groups of well-being-based smart home technologies.

## 3. CONCEPTUAL FRAMEWORK AND HYPOTHESIS DEVELOPMENT

### 3.1. Performance, effort expectancy, and behavioral intention to use

Venkatesh *et al.* (2012) proposed the UTAUT model as the most effective integrated model for analyzing technology acceptance and behavioral intention of usage (BIU). BIU refers to the motivational factors that influence a given behavior, where the stronger the intention to perform the behavior is, the more likely it is that the behavior will be performed (Venkatesh *et al.*, 2012). Within the UTAUT model, according to regulatory theory (Higgins, 1997) rather than utilitarian prevention-orientation variables, performance expectancy (PE) and effort expectancy (EE) impact the behavioral intention of use (BIU) of the new technology (e.g., Venkatesh *et al.*, 2012). PE refers to users' feelings of improved performance when using new technology, and EE refers to how a person believes that using a particular technology will be free of effort or have a good degree of ease (Venkatesh *et al.*, 2003). PE and EE refer to utilitarian benefits. These utilitarian benefits are important aspects toward acceptance of new technologies, including smart homes; these aspects are related to cognitive evaluation, product quality, rationality, decision effectiveness, goal orientation, economic value, convenience (e.g., effort and performance expectancy) and serve to drive an individual's intention to use (Venkatesh *et al.*, 2012). According to a recent survey (Statista, 2021), 70% would adopt a smart home to make life easier. Indeed, in the case of smart homes, previous research has pointed out that some of the most important perceived utilitarian benefits are related to time gain benefits (Blut *et al.*, 2021). The more users perceive utilitarian benefits from smart home functions, the greater they will be interested in using and exploiting the function to maximize these benefits. The UTAUT model postulates that the easier a technology is to use (high EE), the higher the performance expectancy will be. Thus, the higher the EE of a smart home is, the more easily smart home technology can be used, and the more this should engender positive experiences and capabilities and help users in their daily lives and usage; thus, subsequently, EE of a smart home should have a positive impact on PE. Furthermore, research has also suggested that smart homes may also have benefits related to reducing energy consumption costs that may push consumers to use various functions, thereby representing an approach to improving usage/performance efficiency (Schill *et al.*, 2019). We thus assume that the perceived time- and energy-saving benefits increase PE and the propensity to use the smart homes' functions to maximize one's gain. The UTAUT model postulates that PE positively influences BI. Thus, the higher PE is, the more smart home technology should engender positive experiences and capabilities and help users in their daily lives and usage; subsequently, PE should have a positive impact on the BIU of smart homes (Venkatesh *et al.*, 2012). Thus, we posit the following hypotheses:

**H1a:** A high effort expectancy of a smart home has a positive effect on its performance expectancy.

**H1b:** A high performance expectancy of a smart home has a positive effect on its behavioral intention of use.

### 3.2. Subjective user well-being

According to regulatory focus theory (Higgins, 1997), users have not only utilitarian but also affective promotion-oriented motivations closely related to well-being and health (Ashraf & Thongpapanl, 2015). Indeed, a study by Statista (2021) shows that fun/happiness and user well-being (57%) are other main benefits that are reported when researching the usage of smart homes. Subjective well-being (SWB) is described as the degree to which consumers perceive experiences in positive ways through cognitive judgments and affective reactions without objective facts (Diener, 1984); SWB can be linked to physical and mental health, positive moods and emotions, and a pleasant affect, all of which refer to positive emotions, life satisfaction and quality of life (Diener *et al.*, 1985). Research shows that SWB affects consumers' technology choices and usage (Diener & Chan, 2011). Therefore, consumer subjective well-being is attracting an increased level of attention in academia and transformative marketing research (Sirgy, 2012). It is a significant factor driving the use of technology (Kim *et al.*, 2014). When consumers adopt new technology, they want to experience and enhance their subjective well-being, happiness, life satisfaction, and trust through its usage (Li *et al.*, 2014). Consumers' SWB may be shaped by using new technologies (Zhong & Mitchell, 2012), such as AI-based smart homes, and by increasing user security through automation and sensors. Moreover, the use of smart connected objects with health features has been shown to improve SWB (Voss *et al.*, 2003). Indeed, smart homes cope with situations requiring complex observations and interactions, such as temperature and air quality control as well as safety, which are challenging for humans. Smart homes can also have great environmental benefits related to reducing energy consumption and greenhouse gas emissions (Schill *et al.*, 2019). Consequently, smart home usage should increase the level of user comfort and thus physical and psychological SWB through a decrease in perceived risk. The higher the level of user-expected SWB present when using a smart home is, the greater the users' positive mental, psychological and physiological representations about technology use will be enhanced (Davis & Pechmann, 2013). These benefits in turn should have a positive effect on smart homes' behavioral intention of use (Kim *et al.*, 2014). We thus hypothesize the following:

**H2:** Subjective well-being created by a smart home has a positive effect on its behavioral intention of use.

In this context, when adopting new technology, ease of use and performance benefits are also related to subjective well-being (Kim *et al.*, 2020). Better self-knowledge and self-management of quality of life should positively influence performance expectancy by improving efficiency and productivity. Therefore, smart homes should fit into users' daily routines and achieve performance expectancy through sensors that measure, for example, optimal room temperatures or lighting, which should consequently improve health and SWB (Voss *et al.*, 2003). Thus, performance expectancy should have a positive impact on SWB (Kim *et al.*, 2020). Thus, we hypothesize the following:

**H3:** The performance expectancy of a smart home has a positive effect on subjective well-being.

Technology safety and trust are also highly ranked according to the study of Statista (2021) about smart homes. Indeed, privacy concerns, fear of technology, addiction, and potential loss of control are perceived by approximately 50% as main barriers. Stress can be increased through fears regarding the IoT and smart connected technologies, such as smart homes. More precisely, health risks linked to electromagnetic radiation or the consequences of addiction, privacy concerns, risks of hacking, data stealing, and loss of control are sources of potential doubt and stress (Statista, 2021). Consumer decisions involve beliefs about potential risks since consequences cannot be anticipated with certainty. This explains the confidence or anxiety that people feel about the safety of using AI-based smart homes and the extent to which users would rely on their technology. Therefore, cognitive factors, based on utilitarian, prevention-oriented goals (according to regulatory focus theory) (Avnet & Higgins, 2006; Higgins, 1997), such as technology trust, privacy protection, and technology security, are highly relevant in recent technology acceptance models about AI and service robots (Ostrom *et al.*, 2019; Wirtz *et al.*, 2018).

### 3.3. Technology trust

Key drivers of technology acceptance and usage come from the trust-privacy literature (Lancelot Miltgen *et al.*, 2013). We have therefore adopted a perspective highlighted by Martin and Murphy (2017), who state that "privacy, security, and other presentation features are among the strongest factors driving purchase intent as mediated by trust". Trust can be especially helpful in overcoming the uncertainty that is often present with technological advances; therefore, trust is an important factor of new technology acceptance (Pavlou, 2003). Technology trust has been defined as the extent to which a person expects that new technology is credible and reliable (McKnight & Chervany, 2001). Trust can be especially helpful in overcoming the uncertainty that is often present with technological advances, so trust is important in the general area of technologies, but it differs for each technology (Pavlou, 2003). Trust in the context of smart homes is a three-dimensional factor explaining "[…] the individual acceptance of smart homes' living assistance systems" (Lankton *et al.*, 2015). The first dimension is concerned with system transparency, which reflects the understanding of how smart homes operate. The second dimension is concerned with technical competence, which is the evaluation of a smart home's technical performance. The third dimension is concerned with situation management, which refers to the belief in being able to regain control at any time. There are two different types of trust in technology, namely, human-like and system-like technology trust (Lankton *et al.*, 2015). Human-like trust is related to integrity, ability, competence, and benevolence, whereas system-like trust refers to reliability, functionality, and helpfulness. Therefore, in the context of AI, IoT, and smart homes, we assume that the more users trust the technology, the more positive the impact on their behavioral intention of use (BIU) and well-being will be. We thus hypothesis the following:

**H4a:** Trust in smart home technology has a positive effect on the behavioral intention to use a smart home.

**H4b:** Trust in smart home technology has a positive effect on subjective well-being due to a smart home.

### 3.4. Perceived privacy concerns

One antecedent that has been largely studied in technology adoption is the issue of privacy concerns (Meyer-Waarden & Cloarec, 2021). Studies have emphasized the importance of privacy in AI, IoT, and smart home technology acceptance (Attour *et al.*, 2020; Ostrom *et al.*, 2019; Wirtz *et al.*, 2018). Privacy concerns comprise an area of study that is receiving increased attention due to the huge amount of personal information that is currently being gathered, stored, transmitted, and published (Cloarec, 2020; Cloarec *et al.*, 2021). Perfect privacy and data protection mechanisms are needed to operate smart homes, as the way that the IoT and AI track and collect personal data for customization can seem intrusive and thus arouse privacy concerns. Privacy concerns are defined as the degree to which users are concerned about the flow and control of the collection, and the storage and sharing of their personal information (Martin &

Murphy, 2017). In the context of smart home adoption, privacy refers to the right of individuals to be able to control the compilation, use, and exposure of their data (Gurumurthy & Kockelman, 2020). Because smart homes collect user data such as daily routines, behaviors, and health information, privacy concerns have been identified as one of the greatest barriers to such smart technology acceptance (Malhotra *et al.*, 2004). When users perceive risks regarding how their data are collected and used by smart homes, they tend to develop feelings of stress linked to a lack of control that decrease their trust in that technology (Hong & Thong, 2013). We propose that privacy concerns reduce the level of user trust due to fears related to data privacy and that consumers thus experience an adverse emotional reaction toward smart homes that evokes fear and confusion (Gurumurthy & Kockelman, 2020). Therefore, we assume that privacy concerns hurt trust in AI-based smart homes (Martin & Murphy, 2017), and we hypothesize the following:

**H5:** Privacy concerns about a smart home have a negative effect on trust in smart home technology.

### 3.5. Perceived technology security

Recent accidents in the autonomous car sector have initiated concerns regarding users' understanding and capability of safely using AI-based technologies (Van Brummelen *et al.*, 2018). As an example, Tesla crashes have suggested that autonomous car systems are not sufficiently reliable at this time to allow full automation and loss of driver control. Technology security is thus an important challenge that smart home providers face (Lijarcio *et al.*, 2019). More work needs to be done to fully understand the security of the human-AI-based technology interaction before home automation can become a reality (Koopman & Wagner, 2017).

Perceived technology security refers, on the one hand, to how the technology itself reduces human and technology errors, as well as accidents that can harm users' health (Penmetsa *et al.*, 2019). Concerning the security benefits, due to their faster reaction time of AI in comparison to that of humans (Young & Stanton, 2007) and their lower propensity to make mistakes due to distraction, tiredness, and poor physical conditions, it is generally assumed that AI-based smart homes will also reduce accidents, thus providing a safety benefit. On the other hand, perceived technology security refers to mechanisms to avoid network and data transaction attacks or unauthorized access to user accounts (Roca *et al.*, 2009). Perceived technology security thus refers to the capacity of smart homes to be reliable and keep users physically and mentally safe in a given situation. Furthermore, we assume that the perceived technology security benefits reduce users' perceptions of their limited abilities to manage, control, and securely use a smart home (Klobas *et al.*, 2019) by decreasing the number of errors and accidents that could harm users' health. It refers to how smart homes reduce perceived risks of the technology itself and how it might decrease errors and accidents that could harm user health. Slovic (1987) showed that perceived risk is associated with new and unknown technologies, such as AI-based smart homes, and may be based on uncertainty or potentially large consequences of technology failure. Consumer decisions to adopt smart homes thus involve perceived risk since consequences cannot be anticipated with certainty, as consumers face a set of uncertainties about the purchase or rental of a smart home (especially if the product in question is highly priced) (Wang *et al.*, 2020). There are different identified types of perceived technology risks (Featherman & Pavlou, 2003), namely, functional risk, in which smart homes do not meet the user's expectations; physical risk, in which smart homes pose a threat to the physical well-being or health of the user or others; and psychological risk, in which smart homes affect the uncertainty and mental well-being of the user. People still perceive risks in putting their safety in the hands of AI-based smart technologies (autonomous cars or smart homes) for fear of technical or system failures. More precisely, technology security risks for smart homes are linked to health risks due to loss of control in the residence, and risks of hacking are sources of potential doubt and stress. This explains the confidence or anxiety that people feel about the safety of using smart homes and the extent to which users are willing to rely on such technology. The adoption and usage of AI-based smart homes are thus related to concerns over how reliable they will be, in addition to uncertainty about how smart homes will react in critical situations. Many users of AI-based technologies seem unwilling to give up their level of control and thus are less likely to adopt them (Asgari & Jin, 2019). Therefore, perceived technology security is an important issue that makes people resist adopting new technology (Kim *et al.*, 2017) and is a recurrent question related to AI-based technology adoption/usage. Indeed, in the case of smart homes and cars, previous research has pointed out that one of the most important perceived utilitarian benefits is related to security improvement (Hohenberger *et al.*, 2016). Therefore, the perceived technology security of smart homes should impact user attitudes and perceived behavioral control. If users believe that a smart home makes their daily life safer by managing and reducing human errors in complicated or unexpected situations, there should be a positive impact on smart home technology trust (Klobas *et al.*, 2019). Therefore, we hypothesize as follows:

**H6:** The perceived security of the technology used in a smart home has a positive effect on trust in smart home technology.

## 3.6. National culture and country technology readiness

The most popular conceptualization of national culture has been Hofstede's categorization, which includes six dimensions: uncertainty avoidance, individualism/collectivism, power distance, long term/short term orientation, indulgence, and masculinity/femininity cultures (Hofstede, 1993). The dimensions a) uncertainty avoidance (UA) and b) masculinity/femininity thus appear of particular interest for new technology adoption (Srite & Karahanna, 2006), such as smart homes. Due to the unique innovative nature of smart homes and their innovativeness (i.e., the concept is abstract so that consumers cannot try, touch, or feel the product), it is perceived as risky, and UA appears to be a highly relevant concept because the implementation of new technology is likely to be accompanied by uncertainty (Venkatesh & Zhang, 2010). UA refers to the degree to which members of a given culture perceive and react to undefined risks, threats, and unknown situations, as well as their resistance, to try new products or technologies and to retain previous consumption patterns. Hence, users of countries with low (high) UA are (not) open to change and are more (less) likely to take risks (Gilly *et al.*, 2012). Hofstede (1993) noted that Western cultures have strong UA (e.g., on a 100-point scale, France and Germany score 86 and 65 on the Hofstede index, respectively), whereas Asian countries based on Confucian culture have lower levels of UA (e.g., China scores 30 on the Hofstede index). Users with high (low) UA have high (low) apparent resistance to change and intolerance of new technologies. Additionally, users from high (low) UA cultures demonstrate higher (lower) anxiety levels toward change, and new technologies have a high (low) need for control, which means that having a set structure in all aspects of their life helps. Therefore, we consider UA to be a moderating variable that may enhance the negative effects of privacy concerns on smart homes' trust and hypothesize the following:

**H7a:** In countries with high (low) levels of UA, the negative effects of privacy concerns on smart homes' trust are stronger (weaker).

In addition to UA, another relevant dimension is masculinity/femininity. A high score (Masculine) on this dimension (e.g., China) indicates that society will be driven by competition, achievement, and success. A low score (Feminine) on the dimension means that the dominant values in society are quality of life and well-being. France scores highest on femininity, followed by Germany and China (Hofstede, 1993). Therefore, dimensions such as trust and subjective well-being should have a higher importance in countries with high femininity, such as France and Germany, and lower importance in China with high masculinity (Gilly *et al.*, 2012). Therefore, we consider UA and femininity to be moderating variables that may enhance the positive effects of trust on consumers' subjective well-being about smart homes. Thus:

**H7b:** In countries with high (low) levels of UA and femininity, the positive effects of trust beliefs on subjective well-being are stronger (weaker).

Consumer behaviors may vary according to distinct (smart home) technology readiness stages, which represent an individual's enthusiasm to use new technology (Blut & Wang, 2020). Technology readiness (TR) consists of optimism, innovativeness, discomfort, and insecurity. An individual at an advanced smart home readiness stage (with high optimism and innovativeness and low discomfort and insecurity) is more likely to use the smart home than an individual at an early smart home readiness stage. Developed countries such as Germany or France are better ranked on the TR index (ranking 8 and 21, respectively) than developing countries such as China (ranking 73). Another more recent indicator is the network readiness index (NRI) framework, which assesses the development degree of a country in terms of future leveraging of technologies, and how people use technology and how they leverage their skills, governance policies for inclusion and safety, impact on well-being, quality of life, and the economy. The NRI has emerged as one of the leading global indices on the use of technology and has been recognized as a global benchmark for assessing the progress and readiness of technology adoption in different countries around the world. The NRI factors enable a country to fully leverage information and communication technologies for inclusive, sustainable growth, competitiveness, and user well-being. The NRI 2019's top 3 performers are Sweden, Singapore, and the Netherlands. Germany, France, and China rank 9th, 18th, and 41st, respectively.

Technology and network readiness provide the basis for our hypothesis that the importance of utilitarian motivations in driving intention to use smart homes across developed (with high TRI/NRI) and developing countries (with low TRI/NRI) may vary due to individuals' varying technology readiness stages. Consumers across different countries with different technology adoption stages perceive different values behind technology use. In the case of developing countries, smart homes are still in their infancy, and consumers are still in the trial-and-error stage (Kim *et al.*, 2017). For example, utilitarian benefits, such as perceived usefulness or performance expectancy, have a stronger influence on technology use for users in developed countries (at an advanced technology adoption stage, such as France, Germany, and ranked higher on the TRI/NRI: 9th, 18th place), whereas those of developing countries (at early stages, such as China, ranked lower on the TRI/NRI: 41st place) focus more on ease of use or effort expectancy (Ashraf & Thongpapanl, 2015; Parasuraman & Colby, 2015). Based on consumers' smart home readiness stages in developed and developing countries and, in line with the aforementioned findings, it is likely that utilitarian motivations, namely, performance expectancy, should play a more (less) important role in driving intention to adopt in developed (developing) countries where individuals are at an advanced (early) smart home readiness stage. On the other hand, effort expectancy should play a less (more) important role in driving performance efficiency in developed (developing) countries where individuals are at an advanced (early) smart home readiness stage. Thus, we hypothesize:

**H8a:** In developed (developing) countries that are at advanced (early) levels of technology/network readiness, the positive effects of performance expectancy on behavioral intention to use smart homes are stronger (weaker).

**H8b:** In developed (developing) countries that are at advanced (early) levels of technology/network readiness, the positive effects of effort expectancy on the performance expectancy of smart homes are weaker (stronger).

Regulatory focus theory found that individuals' regulatory orientations vary between developing and developed countries (Lee *et al.* 2000 & 2010; Lockwood *et al.* 2005). Based on regulatory focus theory (Higgins, 1997), we expect that rationally (affectively) driven prevention-oriented (promotion-oriented) individuals are more likely to have utilitarian (well-being) motivations for using smart homes (Venkatesh & Zhang, 2010). Research has shown that users in developed countries (e.g., the USA, Australia), which are at advanced levels of technology/network readiness, are more promotion-oriented with a high level of motivation for achieving well-being or happiness and engage in activities to seek well-being and happiness (To *et al.*, 2007); on the other hand, users in developing countries, which are at early levels of technology/network readiness, are more prevention- or task-oriented "problem solvers" (involved in goal-oriented activities that include searching for information) and tend to focus more on relevant information, performance and effort efficiency (Ashraf & Thongpapanl, 2015). Thus, we hypothesize:

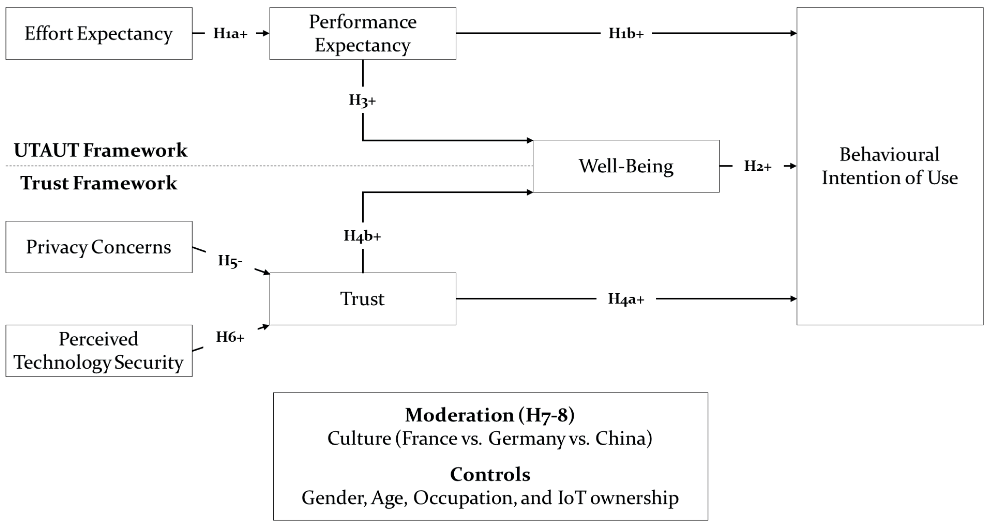
**H8c:** In developed (developing) countries that are at advanced (early) levels of technology/network readiness with promotion-oriented (prevention-oriented) users, the positive effects of subjective well-being on behavioral intention to use smart homes are stronger (weaker).

### 3.7. Control variables

In line with past research, we tested control variables to determine whether they influence their research model (Venkatesh & Zhang, 2010). Gefen and Straub (2003) found that women and men differ in their technology perceptions and suggest that gender should be included in IT diffusion models along with other cultural effects. In the same sense, Venkatesh and Zhang (2010) found that age influences technology adoption. We, therefore, used age, gender, occupation as a proxy for education (Ashraf *et al.*, 2014), and IoT smart object ownership (Gerpott & Paukert, 2013) as control variables. The variables were controlled to assess the linkage between performance expectancy, trust, subjective well-being, and smart home behavioral intention to use.

Our conceptual model is summarized in Figure 1.

**Figure 1: Research model**




## 4. METHODOLOGY

### 4.1. Survey and sample

We conducted an online survey with Qualtrics in December 2019 in France, Germany, and China. Our survey link to the questionnaire was distributed by master's students to their relatives, friends, and colleagues via social media (e.g., Facebook in Europe and We Chat in China) and e-mail based on the snowball principle. The sample was composed of 301 persons, 56.1% women and 43.9% men. The average age was 37.11. The samples in France, Germany, and China are composed of 102, 88, and 111 respondents, respectively. Our sample is thus not representative of the general French, German and Chinese populations in terms of age and sociodemographics (which is the limit of all existing investigations about smart homes; see our literature review in the introduction). Samples drawn from younger populations facilitate comparability, and this generation represents a promising market segment for high-technology smart devices, including AVs, since younger generations tend to be more attracted to new technologies and the Internet than other generations (Ashraf *et al.*, 2014).

**Table 2: Sample description**

| | France (n = 102) | Germany (n = 88) | China (n = 111) | Total (n = 301) | |
|---|---|---|---|---|---|
| | | | | Count | % |
| **Gender** | | | | | |
| Male | 53 | 46 | 33 | 132 | 43.9 |
| Female | 49 | 42 | 78 | 169 | 56.1 |
| **Age** (standard deviation) | 31.8 (13.8) | 37.1 (14.9) | 42 (16.7) | 37.11 (15.76) | |
| **Occupation** | | | | | |
| Student | 49 | 33 | 24 | 106 | 35.2 |
| Workers | 6 | 0 | 3 | 9 | 3 |
| Craft | 4 | 0 | 5 | 9 | 3 |
| Self-employed | 5 | 14 | 0 | 19 | 6.3 |
| Employee, administration | 25 | 12 | 27 | 64 | 21.3 |
| Manager, education, lawyer | 6 | 21 | 30 | 57 | 18.9 |
| Unemployed | 0 | 1 | 22 | 23 | 7.6 |
| Other | 7 | 7 | 0 | 14 | 4.7 |
| **IoT usage** | | | | | |
| Yes | 40 | 42 | 59 | 141 | 46.8 |
| No | 62 | 46 | 52 | 160 | 53.2 |

Before answering the survey, respondents were asked to watch a five-minute video[1] showing a fictional smart home with different connected devices and decisions supervised by AI (room temperature, light dimming, food and diet, and sleeping recommendations) based on previously recorded states of the well-being of the home's residents. This is another contribution of our research, as most of the existing studies have methodological flaws, as they do not use scenarios or use only descriptive verbal scenarios (and not vivid videos to show the smart home environment and its benefits) to frame a still picture for most users of unfamiliar technology (making it hard to understand their functions and benefits).

## 4.2. Measurement instruments

All measurement scales are based on and adapted from previous studies. Responses were collected based on a seven-point Likert scale. To measure effort-performance expectancy and behavioral intention of smart home use, we use the scales found in Venkatesh *et al.* (2012). To measure subjective well-being, we use the scales found in Diener (1984) and Diener and Chan (2011). Trust is measured with the scale from Morgan and Hunt (1994), while privacy concerns are measured with scales from Hong and Thong (2013) and Lutz *et al.* (2017). Perceived technology security is measured with scales from Lijarcio *et al.* (2019) and Yang *et al.* (2018). The moderating impact of uncertainty avoidance

[1] The video can be found on Youtube; https://www.youtube.com/watch?v=sYqjs8TKkOE

(UA) is taken into account by Hofstede's measurements. The UA is high for France (86) and Germany (65) and low for China (30). To classify the three countries into advanced and early smart home readiness stages, we measured individuals' smart home readiness levels across three countries using Parasuraman and Colby's (2015) technology readiness index (TRI). Developed countries such as Germany or France are better ranked on the TR (ranking 8 and 21, respectively) than developing countries such as China (ranking 73). In terms of the Network Readiness Index (2019), Germany, France, and China rank 9th, 18th, and 41st, respectively. Based on the literature (Ashraf *et al.*, 2014; Gerpott & Paukert, 2013), we also added the following control variables: gender, age, occupation, and IoT ownership as a proxy for the experience of smart home IoT technologies.

Detailed scales and items are presented in Table 3. We pretested the questionnaire and the video with thirty international master's students (from Germany, France, and China), and no understanding problems appeared for the items of the questionnaire or the video content. We conducted a confirmatory factor analysis by using the software R 3.6.1 and the lavaan package (Rosseel, 2012); all scales showed satisfactory psychometric properties for reliability ($\alpha > 0.7$), convergent validity (> 0.5) and discriminant validity (HTMT < .85; see Tables 3 and 4) (Henseler *et al.*, 2015). The measurement model achieved good fit according to the usual fit indices: RMSEA < 0.08, CFI > 0.90 and TLI > 0.90 (Table 5).

**Table 3: Reliability (α) and convergent validity of the scales**

| Constructs | α | AVE | Loadings ($p < .001$) | Source |
|---|---|---|---|---|
| **EE – Effort Expectancy** | .87 | .70 | | Venkatesh *et al.* (2012) |
| I would find it easy to use and set up a smart home and its connected services. | | | .77 | |
| I would find it easy to become skillful at using a smart home and its connected services. | | | .92 | |
| I would quickly learn how to use a smart home and its connected services. | | | .83 | |
| **PE – Performance Expectancy** | .95 | .83 | | Venkatesh *et al.* (2012) |
| A smart home and its connected services would be a good assistant in my daily life. | | | .88 | |
| A smart home and its connected services would help me save useful time in my daily life. | | | .92 | |
| A smart home and its connected services would make my everyday life easier. | | | .92 | |
| A smart home and its connected services would increase my efficiency in my daily life. | | | .93 | |
| **BIU – Behavioral Intentions of usage** | .92 | .83 | | Venkatesh *et al.* (2012) |
| Looking at its benefits, I intend to live in a smart home in the future. | | | .96 | |
| Looking at its benefits, If I had access to a smart home, I intend to live in one. | | | .95 | |
| The probability that I rent a smart home in the future is... (1 very low - 10 very high). | | | .87 | |

| | | | | |
|---|---|---|---|---|
| **SWB – Subjective Well-Being** | .96 | .89 | | Diener (1984) and Diener and Chan (2011) |
| If I lived in a smart home my life quality would be improved to ideal. | | | .92 | |
| If I lived in a smart home my feelings of well-being would be improved. | | | .94 | |
| If I lived in a smart home my feelings of happiness would be improved. | | | .96 | |
| **T - Trust** | .92 | .75 | | Morgan and Hunt (1994) |
| I think that a smart home would provide 100% reliable services. | | | .79 | |
| I think a smart home and its connected services would not fail me. | | | .77 | |
| I think a smart home and its connected services would be 100% trustworthy. | | | .94 | |
| I would have 100% confidence in a smart home and its connected services. | | | .92 | |
| **PC – Privacy Concerns** | .96 | .75 | | Hong and Thong (2013) and Lutz *et al.* (2017) |
| I would be concerned about threats to my personal privacy from a smart home. | | | .78 | |
| I would be afraid to use a smart home because cyber pirates could steal my identity and data. | | | .87 | |
| I would be afraid to use a smart home because cyber pirates might hack into my account. | | | .85 | |
| I would be afraid to use a smart home because other people might cyberstalk me. | | | .79 | |
| I would be afraid that a smart home is collecting too much of my personal data. | | | .91 | |
| I would be afraid to use a smart home because other people or firms might publish my personal information without my consent. | | | .88 | |
| I would be afraid to use a smart home because it might insufficiently protect my personal data. | | | .93 | |
| I would be afraid to use a smart home because it might track and analyze my personal data for personalized offers. | | | .89 | |
| I would be afraid to use a smart home because it might share personal data with other firms for purposes I do not know about. | | | .91 | |
| **PTS – Perceived Technology Security** | .87 | .71 | | Lijarcio *et al.* (2019) and Yang *et al.* (2018) |
| A smart home would help make my daily life safer. | | | .77 | |
| A smart home would manage complicated or unexpected situations in my home better than me. | | | .88 | |
| A smart home would help to reduce human errors in complicated or unexpected situations in my home. | | | .86 | |

## Table 4: Discriminant validity HTMT

| | PE | EE | PTS | T | SWB | BIU | PC |
|---|---|---|---|---|---|---|---|
| **PE** | 1.00 | | | | | | |
| **EE** | .61 | 1.00 | | | | | |
| **PTS** | .71 | .42 | 1.00 | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| **T** | .64 | .51 | .70 | 1.00 | | | |
| **SWB** | .80 | .50 | .74 | .75 | 1.00 | | |
| **BIU** | .79 | .57 | .66 | .72 | .83 | 1.00 | |
| **PC** | .24 | .24 | .16 | .30 | .30 | .35 | 1.00 |

EE: Effort Expectancy, PE: Performance Expectancy, PC: Privacy Concerns, PTS: Perceived Technology Security, T: Trust,
SWB: Subjective Well-Being, BIU: Behavioral Intentions of smart home use.

**Table 5: Measurement model fit indices**

| $\chi^2$ | df | RMSEA | CFI | TLI |
|---|---|---|---|---|
| 922 | 356 | 0.073 | 0.942 | 0.934 |

## 5. RESULTS

### 5.1. Model estimation

We estimated the model with the PROCESS macro[2] (Hayes, 2017) for SPSS (see Table 6). The model explains 73% of the behavioral intention of smart home use. In support of H1a, effort expectancy has a positive and significant effect on the performance expectancy of smart home use (b = .58, $p < .001$). In support of H1b, performance expectancy has a positive and significant effect (b = .32, $p < .001$) on the behavioral intention of smart home use. In line with H2, subjective well-being positively influences behavioral intention of smart home use (b = .50, $p < .001$). In line with H3, the performance expectancy of smart home use positively and significantly influences subjective well-being (b = .57, $p < .001$). In line with H4a and H4b, technology trust in smart homes has a positive and significant effect on behavioral intention of smart home use (b = .28, $p < .001$) and subjective well-being (b = .45, $p < .001$). In line with H5 and H6, privacy concerns (b = –.18, $p < .001$) regarding smart homes negatively influence technology trust, while perceived technology security (b = .56, $p < .001$) has a positive effect on trust.

Regarding the control variables, the results confirm that most of our demographic factors do not affect the outcome of the model analysis and are presented in the linkage between smart home intention to use and well-being. The impacts of gender (b = –.20, $p > .05$) and age (b = –.00, $p > .05$) on behavioral intention of smart home use are not significant. We found that being a worker, thus being less educated, leads to lower (b = –1.05, $p < .05$) behavioral intention of smart home use. Conversely, IoT ownership significantly increases performance expectancy (b = .58, $p < .001$) and behavioral intention of smart home use (b = .76, $p < .001$). Being a woman significantly increases (b = .39, $p < .01$) the impact of smart homes' perceived SWB on their behavioral intention to use smart homes.

[2] The PROCESS macro is recommended as a standard method in all eight leading IS journals (i.e., Senior Scholars' Basket of Journals), such as MISQ, EJIS, ISJ, ISR, JMIS. It is specifically tailored for conducting regression-based moderated mediation analyses in SPSS with minimal programming required (Hayes, 2017). The direct and conditional indirect effects can be estimated with a single line of syntax, and the macro estimates all model coefficients, standard errors, test statistics, and bootstrap confidence intervals. The detailed syntax of estimations with PROCESS can be found in the appendix A.

**Table 6: Results of the model estimation**

| | Mediating variables | | | Outcome |
|---|---|---|---|---|
| | PE | T | SWB | BI |
| **Independent variables** | | | | |
| Effort expectancy | **.58*** (H1a)** | | | |
| Privacy concerns | | **–.18*** (H5)** | | |
| Perceived technology security | | **.56*** (H6)** | | |
| **Mediating variables** | | | | |
| Performance expectancy | | | **.57*** (H3)** | **.32*** (H1b)** |
| Trust | | | **.45*** (H4b)** | **.28*** (H4a)** |
| Subjective well-being | | | | **.50*** (H2)** |
| **Control variables** | | | | |
| Gender | $.18^{ns}$ | $.02^{ns}$ | .39** | $–.20^{ns}$ |
| Age | $.01^{ns}$ | .01* | $–.01^{ns}$ | $–.00^{ns}$ |
| Occupation | | | | |
| *Student* | .98* | .84* | $.41^{ns}$ | $.29^{ns}$ |
| *Workers* | 1.41* | $.81^{ns}$ | .97* | –1.05* |
| *Craft* | 1.23* | $.66^{ns}$ | $.74^{ns}$ | $.09^{ns}$ |
| *Self-employed* | $.36^{ns}$ | $.25^{ns}$ | $.54^{ns}$ | $.26^{ns}$ |
| *Employee, administration* | 1.15** | $.60^{ns}$ | $.52^{ns}$ | $.21^{ns}$ |
| *Manager, education, lawyer* | 1.08** | .72* | $.51^{ns}$ | $.14^{ns}$ |
| *Unemployed* | 1.52** | $.73^{ns}$ | 1.15** | $.05^{ns}$ |
| IoT ownership | .58*** | $.15^{ns}$ | $.08^{ns}$ | .76*** |
| **$R^2$** | .39*** | .47*** | .70*** | .73*** |

PE: Performance Expectancy, T: Trust, SWB: Subjective Well-Being, BIU: Behavioral Intentions of smart home use.
***$p < .001$, **$p < .01$, *$p < .05$, ns: not significant

## 5.2. Moderation analyses by country

The results of the moderation analysis by country are shown in Table 7. To account for the smaller size of the three subsamples, the coefficients are estimated with 5000 bootstrap samples. It should be noted that the variance explained by our model is high (73%) and in line with the research of Venkatesh for the original UTAUT (approximately 60%).

In line with H7a ($DR^2 = .02$, $DF_{(2, 283)} = 6.12$, $p < .01$), in countries with high levels of uncertainty avoidance (UA) according to Hofstede, such as France and Germany, which score 86 and 65, respectively, the negative effects of privacy concerns on smart homes' trust are stronger ($b_{Fr} = –.18$, $p < .04$ vs. $b_{Ger} = –.39$, $p < .001$) than in China ($b_{Chi} = –.05$, $p > .05$), a country with low UA that scores 30. Furthermore, in line with H7b countries with high levels of uncertainty avoidance and femineity (France and Germany), the impact of trust on subjective well-being ($DR^2 = .01$, $DF_{(2, 283)} = 4.33$, $p < .05$) is higher ($b_{Fr} = .54$, $p < .001$ vs. $b_{Ger} = .49$, $p < .001$) than in China ($b_{Ch} = .28$, $p < .001$), a country with low UA and femineity. The positive impact of performance expectancy on the behavioral intention of smart home use is not significantly moderated by a country's Technology Readiness Index-TRI and Network Readiness Index-NRI ($DR^2 = .00$, $DF_{(2, 280)} = 2.26$, $p > .05$), thus rejecting H8a. There is no difference between developed countries (rankings Germany 8th, France 21st, respectively) and developing countries (like China with a ranking 73) and Network Readiness Index-NRI (Germany, France, and China are ranked, respectively on the 9th, 18th place, and 41st place); therefore, in developed countries that are at advanced levels of TRI/NRI, the positive effects of performance expectancy on the behavioral intention of smart home use are not stronger than in developing countries with low TRI/NRI. We also reject H8b ($DR^2 = .00$, $DF_{(2, 284)} = .18, p > .05$), as in developed countries that are at advanced levels of TRI/NRI, the positive effects of effort on the performance expectancy of smart homes are not stronger than in developing countries with low TRI/NRI. Finally, we reject H8c ($DR^2 = .00$, $DF_{(2, 283)} = 2.18, p > .05$), as in developed countries, which are at advanced levels of TRI/NRI, the positive effects of subjective well-being – on the behavioral intention of smart home use are not stronger than in developing countries with low TRI/NRI.

**Table 7: Results of the moderation analysis by country**

| | **DR² (Country differences)** | **F-test** | **France** | **Germany** | **China** |
|---|---|---|---|---|---|
| PC → T | | $\Delta F_{(2, 283)} = 6.12$ | –.18* | –.39*** | –.05ns |
| T → SWB | **.01* (H7b)** | $\Delta F_{(2, 283)} = 4.33$ | .54*** | .49*** | .28*** |
| PE → BIU | $.00^{ns}$ (H8a) | $\Delta F_{(2, 280)} = 2.26$ | .33*** | .40*** | .23ns |
| EE → PE | $.00^{ns}$ (H8b) | $\Delta F_{(2, 284)} = .18$ | .42*** | .58*** | .62*** |
| SWB → BIU | $.00^{ns}$ (H8c) | $\Delta F_{(2, 283)} = 2.18$ | .41*** | .45* | .27*** |

PE: Performance Expectancy, PC: Privacy Concerns, T: Trust, SWB: Subjective Well-Being, BIU: Behavioral Intentions of smart home use.
*** $p < .001$, ** $p < .01$, *$p < .05$, ns: not significant

## 5.3. Additional mediation analysis

We carried out an additional mediation analysis with 5,000 bootstrap samples (see Table 8). The results show six significant mediating effects (the 99% confidence interval [CI] excludes 0). (1) The positive indirect effect between effort expectancy and behavioral intention of smart home use, via performance expectancy, is positive (b = .18, $p < .01$, 99% CI [.0636, .3194]). (2) The positive indirect effect runs from effort expectancy to behavioral intention of smart home use via performance expectancy and subjective well-being (b = .16, $p < 0.01$, 99% CI [.0743, .2779]). (3) The negative indirect effect runs from privacy concerns to BI of smart home use via trust (b = –.05, $p < .01$, 99% CI [–.1162, –.0090]). (4) The negative indirect effect runs from privacy concerns to the behavioral intention of smart home use via trust and subjective well-being (b = –.04, $p < .01$, 99% CI [–.0866, –.0104]). (5) The positive indirect effect runs from perceived technology security to behavioral intention of smart home use via trust (b = .15, $p < .01$, 99% CI [.0407, .2987]). (6) The positive indirect effect runs from perceived technology security to behavioral intention of smart home use via trust and subjective well-being (b = .13, $p < .01$, 99% CI [.0606, .2190]). The mediation analysis also shows that the indirect effects are stronger for effort expectancy (.16 and .18) than for privacy concerns (–.04 and –.05) or perceived technology security (.13 and .15).

**Table 8: Results of the mediation analysis**

| Mediation | *b* | 95% CI | | 99% CI | |
|---|---|---|---|---|---|
| | | Lower | Upper | Lower | Upper |
| EE → PE → BIU | .18** | .0882 | .2837 | .0636 | .3194 |
| EE → SWB → BIU | –.01$^{ns}$ | –.0744 | .0466 | –.0955 | .0687 |
| EE → PE → SWB → BIU | .16** | .0936 | .2489 | .0743 | .2779 |
| PC → T → BIU | –.05** | –.0964 | –.0163 | –.1162 | –.0090 |
| PC → T → SWB → BIU | –.04** | –.0732 | –.0159 | –.0866 | –.0104 |
| PTS → T → BIU | .15** | .0644 | .2628 | .0407 | .2987 |
| PTS → T → SWB → BIU | .13** | .0693 | .1951 | .0606 | .2190 |

EE: Effort Expectancy, PE: Performance Expectancy, PC: Privacy Concerns, PTS: Perceived Technology Security, T: Trust, SWB:
Subjective Well-Being, SBB: Subjective Bad-Being, BIU: Behavioral Intentions of smart home use.
**$p < .01$, ns: not significant

## 6. DISCUSSION OF THE RESULTS

First, we confirm regulatory focus theory, which argues that there are two types of goals when making decisions to adopt a smart home: utilitarian, prevention-oriented goals, and affective, promotion-oriented goals (Higgins, 1997). A utilitarian prevention focus involves rationality, ease of use, performance, security, and protection, whereas a promotion focus involves affective goals, such as happiness and well-being (Avnet & Higgins, 2006). Based on our results, we conclude that smart home choices are based on both rational utilitarian, prevention-oriented and affective, promotion-oriented driven motivations for using smart homes (Venkatesh & Zhang, 2010). According to regulatory focus theory (Higgins, 1997), we find that the utilitarian path of smart home adoption involving performance- and effort efficiency, security, and protection is completed by an affective, promotion-oriented path based on values such as well-being and health-related features (To *et al.*, 2007). In line with the literature, our research shows the positive indirect effect between effort expectancy and the behavioral intention of smart home use via performance expectancy (Venkatesh *et al.*, 2012). Therefore, the functionality and ease of operation of a smart home influence users' well-being when the technology is perceived to increase utilitarian-oriented performance expectancy.

Second, in line with consumer behavior and regulatory focus theory, we show that this utilitarian path through performance expectancy and effort expectancy is not sufficient to explain smart home technology adoption and usage, as does a hybrid utilitarian-prevention and promotion-oriented path, where effort expectancy has an indirect positive effect on well-being via the mediation of performance expectancy (Kim & Sundar, 2014). Furthermore, utilitarian performance expectancy has a positive effect on well-being, which has a positive impact on smart home behavioral intention of usage. We thus show that within the promotion-oriented path, beyond performance- and effort expectancy, consumers look for subjective well-being while using technology (Sirgy, 2012). Another utilitarian and the prevention-oriented path runs from perceived technology security to behavioral intention of smart home use via mediator trust (Klobas *et al.*, 2019). Subsequently, again, a promotion-oriented path goes from technology trust that positively influences physical/psychological well-being through a decrease in perceived risks; this, in turn, has a positive effect on smart home behavioral intention of use (Kim *et al.*, 2014). On the other hand, again on a hybrid utilitarian-prevention and promotion-oriented path, there is a negative indirect effect that runs from privacy concerns to the behavioral intention of smart home use, via the mediators (i.e., technology trust and subjective well-being). This is in line with the literature that confirms these negative links between perceived risks of technologies and intention to adopt (Ostrom *et al.*, 2019; Pavlou, 2003; Wirtz *et al.*, 2018). The mediation analysis also shows that the indirect effects are stronger for effort expectancy than for privacy concerns or perceived technology security. As a result, we conclude that promotion-oriented well-being acts as a mediator between utilitarian prevention benefits and behavioral intention related to smart home use (Kim *et al.*, 2020).

Our cross-cultural analyses in three countries enhance the validity of our results and offer interesting insights. Specifically, Hofstede's dimensions of uncertainty avoidance (UA) and masculinity/femininity appear of particular interest for new technology adoption, such as smart homes (Ashraf & Thongpapanl, 2015; Hofstede, 1993). Hence, in line with the literature (Srite & Karahanna, 2006), we found that in countries with high (low) levels of UA, consumers are less (more) likely to take risks, have high (low) apparent resistance to change, and are intolerant to new technologies (Gilly *et al.*, 2012). In France and Germany, high levels of UA thus increase the negative impact of privacy concerns on technology trust. In China, an Asian country based on Confucian culture with lower levels of UA, perceived privacy risks prove to have no negative impact on trust and well-being. Past research confirms this result, indicating Western (US) users' concerns about losing privacy control in a smart home environment are higher than users' concerns in China (Ji & Chan, 2020). This is probably also related to the stronger *General Data Protection Regulation* (GDPR) in Europe compared to the insufficient legal context in China. Chinese users pay less attention to privacy protection issues related to smart technology because of the legal deficiency regarding the protection of people's privacy or data collection through smart city infrastructure (Ji & Chan, 2020). Furthermore, due to cultural and social differences, as well as the prevalence of surveillance culture, Chinese users are not as sensitive as Europeans or Americans about their privacy rights. Furthermore, in line with the literature (Srite & Karahanna, 2006), in France and Germany, countries with high levels of UA, the impact of trust on subjective well-being is higher than in China, a country with low UA.

The results can also be supported by the fact that developed countries ranked higher both on the Technology Readiness Index (TRI; rankings Germany 8th, France 21st, respectively) than developing countries like China (ranking 73rd) and Network Readiness Index (NRI-Germany, France, and China rank, respectively on the 9th, 18th place, and 41st place) privacy concerns are higher and thus trust plays a more important role (Ashraf & Thongpapanl, 2015). This is in line with research that has shown that users in developed countries with advanced levels of technology/network readiness are more promotion-oriented according to regulatory focus theory with a high level of motivation for achieving trust, well-being, and happiness (To *et al.*, 2007); on the other hand, regulatory focus theory states that users in developing countries with early levels of technology/network readiness are more prevention or task-oriented "problem solvers" and tend to focus more on relevant information, performance and effort efficiency (Ashraf & Thongpapanl, 2015). Indeed, the literature shows that in China, the top three highest rankings of smart home attributes are all associated with utilitarian factors of economic performance related to cost reduction (Ji & Chan, 2020). This is not confirmed by our results, as the positive impact of performance expectancy on the behavioral intention of smart home use is not moderated by a country's TTRI and NRI. In developed countries, such as France and Germany, which are at advanced levels of TRI/NRI, the positive effects of performance expectancy on the behavioral intention of smart home use are not weaker than in developing countries, such as China, with low TRI/NRI. Finally, the moderating role of technology readiness between well-being and behavioral intentions to use smart homes seems to play a major role in adopting smart homes, in line with the literature (Kim *et al.*, 2020). High technology readiness fosters optimism and innovativeness and reduces discomfort and insecurity and is thus positively associated with technology acceptance. That is, consumers in countries with optimism related to higher TRI/NRI (France and Germany) are more likely than their counterparts with low optimism to adopt new smart home technology.

## 7. CONTRIBUTIONS

### 7.1. Theoretical contributions

Smart home technologies and devices will have a major impact on smart city development, enhancing users' experiences and well-being. Despite the growing interest in and importance of smart cities and smart homes, management science research still shows major gaps in terms of the reasons for adoption, and a theoretically integrated model has not been developed and tested. To fill this void, we have created and examined a conceptually integrated model incorporating UTAUT (Venkatesh *et al.*, 2012) and other technology acceptance theories (Ostrom *et al.*, 2019; Wirtz *et al.*, 2018), regulatory focus theory (Higgins, 1997), uses and gratifications theory (Katz *et al.*, 1973), and technology readiness (Parasuraman & Colby, 2015) to explain why people in different countries would adopt smart homes. We found the following results:

With this model, we first confirm regulatory focus theory and show that two, not necessarily distinct, but complementary types of goals are pursued when making decisions to adopt a smart home: utilitarian, prevention-oriented goals, involving rationality, ease of use, performance, security and protection, and affective, promotion-oriented goals, involving affection, happiness, and well-being (Avnet & Higgins, 2006). We thus contribute to the literature and show that smart home choices are based on rational utilitarian, prevention-oriented and affective, promotion-oriented driven motivations.

Second, the empirical evidence supports the theoretical model's identification of the impact of the theory of uses and gratifications on subjective well-being. Our third major contribution is thus the integration of new variables (Blut *et al.*, 2021) that have rarely been investigated in the TAM or UTAUT literature (namely, well-being, technology trust, privacy concerns, technology security). By doing so, this study deepens our understanding of the most relevant risks and benefits that drive smart home acceptance. We contribute to showing that in the AI and smart home technology acceptance process, trust and well-being are extremely important concepts to enhance the behavioral intention of usage (Pavlou, 2003).

Third, our model contributes to cross-cultural theory and understanding in IS research (Blut *et al.*, 2021; Venkatesh, 2021). The relationship between culture and new technology adoption and use has been identified as one of the most important topics (Kappos & Rivard, 2008). Nevertheless, only a few studies have sought to understand the role of culture and technology adoption (Venkatesh & Zhang, 2010). Our work therefore contributes and advances knowledge in this area. Specifically, this research extends our understanding of smart home technology adoption by not focusing on cultural differences in developed Western and developing Asian countries. Our study shows that smart home acceptance does not work the same way in China as it does in Europe. The effect of privacy concerns in China is different from what is theorized and observed in Europe, indicating that culture is an important contingency factor in the study of technology adoption. We also demonstrate that levels of TRI/NRI differing in developed and developing countries (optimism and innovativeness, technology advancement) moderate smart home users' subjective well-being and behavioral intention of usage (Blut *et al.*, 2021). Our work contributes to the understanding of boundary conditions related to smart home adoption research (Kim *et al.*, 2020).

## 7.2. Managerial implications

To maximize customers' intention to use AI-based smart homes, we recommend that managers focus on three key variables: the smart home's perceived technology security, technology trust, and, consequently, the users' well-being. First, perceived technology security is an influential factor in smart home acceptance, as it leads to trust in the technology as an antecedent of well-being and ultimately use. Second, managers should account for the need to enhance the level of trust that users have in smart homes. Third, our results show that a high level of trust leads to greater consumer well-being, which are both direct antecedents to smart home adoption and usage. Indeed, well-being constitutes a core concept leading to smart home usage. Trust in smart home service providers has become a significant issue, as data-based smart home companies such as Google are rapidly expanding in this sector. Thus, managers should not only communicate the safe and transparent usage of their technical smart home services and devices but also the value they add to the user's perceived security at home. Managers should increase smart home security and reliability, while smart home service providers should apply high-level security technologies to prevent data sharing and leakage. These steps will most likely lead to a high level of trust in both the technology and the company. Furthermore, the more users think that a smart home will increase their health, well-being, and happiness, the likelier they are to use such devices. For managers, this implies focusing on a comparatively small number of concepts encompassed by well-being regarding the use of smart homes because well-being has an even greater effect on smart home adoption and usage than trust. Hence, managers must be aware of the fact that customers expect to live better, more easily, and more happily using new technologies, including AI-based smart homes, that simplify their lives, increase their quality of life, and decrease risks caused by feelings of insecurity and stress.

In addition to utilitarian-oriented benefits such as smart home control functionality, ease of use, convenience, time savings, cost/energy efficiency (e.g., control of heating and lighting systems by remote; preheating homes), managers and policymakers should also emphasize other types of affective benefits, such as their m-health/well-being-management potential. Improving health (e.g., physiological monitoring, communications with health care providers) is a promising market opportunity, as the market for m-health and elderly health care is increasing dramatically. The global smart health care market is projected to grow at an annual rate of 16.2% from 2020 to 2027. More than 40,000 health applications are downloadable (Krebs & Duncan, 2015). Managers and policymakers should also aim to decrease perceived sociotechnical risks of dependence on technologies as well as perceived technology and privacy issues to increase consumer trust. In Europe, as prospective users are concerned about data and privacy issues, managers should support smart home development by including and promoting features and guidelines on data and privacy protection to build consumer trust. Policymakers should further increase data collection and usage protection laws and measures in the General Data Protection Regulation (GDPR) in Europe. However, the reality in firms is different, as data security is only rarely mentioned in marketing materials: only 8% of UK companies mention that data security is an important smart home communication issue (Wilson *et al.*, 2017).

Our cultural analyses provide further interesting managerial insights into sales arguments. Specifically, uncertainty avoidance (UA) appears to be an interesting segmentation variable for smart home communication and positioning. In Western developed countries (e.g., Europe, US, Canada) with high UA, a special focus should be given to advertising arguments that decrease the negative impact of privacy concerns and increase the positive influence of technology trust on consumers' intention of use of smart homes. However, in developing Asian countries with lower levels of UA (e.g., China), arguments against perceived privacy risks prove to be less relevant for consumers' intention of use. Nevertheless, sales arguments about technology trust and well-being through smart homes are very important in all these countries.

## 8. LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

Although the findings of this study provide meaningful insights into the adoption of AI-based smart homes, certain limitations (that potentially might bias managerial implications) must be addressed. First, the sample may not perfectly represent the actual smart home target market, as only persons who do not already use a smart home were surveyed. Furthermore, the sample is based on snowball sampling and is thus not demographically representative. Therefore, future studies should use larger and demographically representative sample sizes that include respondents who already use smart home technologies to ensure the generalizability of the results. Furthermore, as the majority of the research has been conducted in developed and not in developing countries, future research should also replicate our study in different countries with less or higher TRI and NRI to contribute to the theory of acceptance of smart homes by integrating cognitive (utilitarian, financial, perceived risks), health, psychological, emotional, and affective factors that could drive adoption or psychological resistance. The different cultural, economic, and geopolitical contexts might influence norms, attitudes, beliefs, and intentions about smart homes. Therefore, future research needs to investigate and compare the perception of the benefits and services of smart homes in different countries.

Respondents only expressed their views on smart home technology after watching a short video, which might not have provided enough information to fully understand all the benefits and risks of a smart home. Indeed, there is a bias, as the respondents expressed their views only on AI-powered smart homes after watching a short video but had not yet used smart homes and thus might have biased a priori perceptions and attitudes toward smart homes. Unfortunately, we could not control these a priori perceptions and attitudes (as is the case in most academic studies about new products, services, and technologies, including smart homes). Hence, further research is needed to control these a priori perceived risks and benefits and to gain a more in-depth understanding of how perceptions of smart homes shape the behavioral intention to use smart homes. Future studies should thus be carried out with innovative methodological approaches, with real smart homes and virtual reality as well as simulation, and put respondents in actual real-life use situations.

Another limitation is related to the smart home type investigated. We investigated health/well-being-oriented smart homes and did not test how adoption and usage depend on the type of AI-powered smart home. Future studies should work on surveillance homes that aim to process data to forecast and alert residents in case of upcoming disasters or security interventions and, above all, on ecological environment-oriented smart homes that promote environmental sustainability by enabling residents to monitor, control, and reduce their energy consumption. They should differentiate and test cross effects according to the profile of respondents. Future studies also need to take into account the different types of smart homes, as contextual differences may determine the distinctive factors to be exhibited in the acceptance and adoption process.

Finally, considering internationalization as highly important and given that the interplay between culture and technology adoption is important and given the limited research on these topics, future research should aim to advance our understanding in this area by refining our study. Although we acknowledge the important role of culture in affecting technology adoption, we did not measure other cultural values of Hofstede's framework, such as collectivism/individualism, social influence, power distance, and a long-term orientation, in the three countries where we conducted the study. This is an oversimplified view, as there is strong cultural heterogeneity within countries. Little research has examined cultural values at the individual level in technology adoption. Future research should thus examine the role of culture at the individual level, as it is important to understand how individuals' cultural value systems might impact their behaviors.

## REFERENCES

Aldossari, M. Q., & Sidorova, A. (2020). Consumer Acceptance of Internet of Things (IoT): Smart Home Context. *Journal of Computer Information Systems*, *60*(6), 507–517. https://doi.org/10.1080/08874417.2018.1543000

Asgari, H., & Jin, X. (2019). Incorporating Attitudinal Factors to Examine Adoption of and Willingness to Pay for Autonomous Vehicles. *Transportation Research Record: Journal of the Transportation Research Board*, *2673*(8), 418–429. https://doi.org/10.1177/0361198119839987

Ashraf, A. R., & Thongpapanl, N. (Tek). (2015). Connecting with and Converting Shoppers into Customers: Investigating the Role of Regulatory Fit in the Online Customer's Decision-making Process. *Journal of Interactive Marketing*, *32*, 13–25. https://doi.org/10.1016/j.intmar.2015.09.004

Ashraf, A. R., Thongpapanl, N. (Tek), & Auh, S. (2014). The Application of the Technology Acceptance Model under Different Cultural Contexts: The Case of Online Shopping Adoption. *Journal of International Marketing*, *22*(3), 68–93. https://doi.org/10.1509/jim.14.0065

Attour, A., Baudino, M., Krafft, J., & Lazaric, N. (2020). Determinants of energy tracking application use at the city level: Evidence from France. *Energy Policy*, *147*, 111866. https://doi.org/10.1016/j.enpol.2020.111866

Avnet, T., & Higgins, E. T. (2006). How Regulatory Fit Affects Value in Consumer Choices and Opinions. *Journal of Marketing Research*, *43*(1), 1–10. https://doi.org/10.1509/jmkr.43.1.1

Balta-Ozkan, N., Boteler, B., & Amerighi, O. (2014). European smart home market development: Public views on technical and economic aspects across the United Kingdom, Germany and Italy. *Energy Research & Social Science*, *3*, 65–77. https://doi.org/10.1016/j.erss.2014.07.007

Bangkok Post. (2021). *Smart-City Living Marks Another Milestone for Thailand 4.0*. https://www.bangkokpost.com/business/2049051/smart-city-living-marks-another-milestone-for-thailand-4-0

Bao, H., Chong, A. Y. L., Ooi, K. B., & Lin, B. (2014). Are Chinese consumers ready to adopt mobile smart home? An empirical analysis. *International Journal of Mobile Communications*, *12*(5), 496. https://doi.org/10.1504/IJMC.2014.064595

Batty, M., Axhausen, K. W., Giannotti, F., Pozdnoukhov, A., Bazzani, A., Wachowicz, M., Ouzounis, G., & Portugali, Y. (2012). Smart cities of the future. *The European Physical Journal Special Topics*, *214*(1), 481–518. https://doi.org/10.1140/epjst/e2012-01703-3

Bhati, A., Hansen, M., & Chan, C. M. (2017). Energy conservation through smart homes in a smart city: A lesson for Singapore households. *Energy Policy*, *104*, 230–239. https://doi.org/10.1016/j.enpol.2017.01.032

Blut, M., Chong, A., Tsiga, Z., & Venkatesh, V. (2021). Meta-Analysis Of The Unified Theory Of Acceptance And Use Of Technology (UTAUT): Challenging Its Validity And Charting A Research Agenda In The Red Ocean. *Journal of the Association for Information Systems*.

Blut, M., & Wang, C. (2020). Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage. *Journal of the Academy of Marketing Science*, *48*(4), 649–669. https://doi.org/10.1007/s11747-019-00680-8

Camero, A., & Alba, E. (2019). Smart City and information technology: A review. *Cities*, *93*, 84–94. https://doi.org/10.1016/j.cities.2019.04.014

Caragliu, A., Del Bo, C., & Nijkamp, P. (2011). Smart Cities in Europe. *Journal of Urban Technology*, *18*(2), 65–82. https://doi.org/10.1080/10630732.2011.601117

Chan, M., Estève, D., Escriba, C., & Campo, E. (2008). A review of smart homes—Present state and future challenges. *Computer Methods and Programs in Biomedicine*, *91*(1), 55–81. https://doi.org/10.1016/j.cmpb.2008.02.001

Cloarec, J. (2020). The Personalization–Privacy Paradox in the Attention Economy. *Technological*

*Forecasting and Social Change*, *161*, 120299. https://doi.org/10.1016/j.techfore.2020.120299

Cloarec, J., Meyer‐Waarden, L., & Munzel, A. (2021). The personalization–privacy paradox at the nexus of social exchange and construal level theories. *Psychology & Marketing*, mar.21587. https://doi.org/10.1002/mar.21587

Davis, B., & Pechmann, C. (2013). Developing theory to mobilize efforts that improve consumer and societal well-being. *Journal of Business Research*, *66*(8), 1168–1170. https://doi.org/10.1016/j.jbusres.2012.08.008

De Silva, L. C., Morikawa, C., & Petra, I. M. (2012). State of the art of smart homes. *Engineering Applications of Artificial Intelligence*, *25*(7), 1313–1321. https://doi.org/10.1016/j.engappai.2012.05.002

Diener, E. (1984). Subjective Well-Being. *Psychological Bulletin*, *95*(3), 542–575. https://doi.org/10.1037//0033-2909.95.3.542

Diener, E., & Chan, M. Y. (2011). Happy People Live Longer: Subjective Well-Being Contributes to Health and Longevity. *Applied Psychology: Health and Well-Being*, *3*(1), 1–43. https://doi.org/10.1111/j.1758-0854.2010.01045.x

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Ehrenhard, M., Kijl, B., & Nieuwenhuis, L. (2014). Market adoption barriers of multi-stakeholder technology: Smart homes for the aging population. *Technological Forecasting and Social Change*, *89*, 306–315. https://doi.org/10.1016/j.techfore.2014.08.002

Featherman, M. S., & Pavlou, P. A. (2003). Predicting e-services adoption: a perceived risk facets perspective. *International Journal of Human-Computer Studies*, *59*(4), 451–474. https://doi.org/10.1016/S1071-5819(03)00111-3

Foroudi, P., Gupta, S., Sivarajah, U., & Broderick, A. (2018). Investigating the effects of smart technology on customer dynamics and customer experience. *Computers in Human Behavior*, *80*, 271–282. https://doi.org/10.1016/j.chb.2017.11.014

Gefen, D., Karahanna, E., & Straub, D. W. (2003). Trust and TAM in Online Shopping: An Integrated Model. *MIS Quarterly*, *27*(1), 51–90.

Gerpott, T. J., & Paukert, M. (2013). Determinants of willingness to pay for smart meters: An empirical analysis of household customers in Germany. *Energy Policy*, *61*, 483–495. https://doi.org/10.1016/j.enpol.2013.06.012

Ghayvat, H., Mukhopadhyay, S., Gui, X., & Suryadevara, N. (2015). WSN- and IOT-Based Smart Homes and Their Extension to Smart Buildings. *Sensors*, *15*(5), 10350–10379. https://doi.org/10.3390/s150510350

Gilly, M. C., Celsi, M. W., & Schau, H. J. (2012). It Don't Come Easy: Overcoming Obstacles to Technology Use Within a Resistant Consumer Group. *Journal of Consumer Affairs*, *46*(1), 62–89. https://doi.org/10.1111/j.1745-6606.2011.01218.x

Gurumurthy, K. M., & Kockelman, K. M. (2020). Modeling Americans' autonomous vehicle preferences: A focus on dynamic ride-sharing, privacy & long-distance mode choices. *Technological Forecasting and Social Change*, *150*, 119792. https://doi.org/10.1016/j.techfore.2019.119792

Harris, C., & Hunter, S. (2016). Smart-home technologies were found to support some domains of independent living when ageing at home: Perspectives of older adult consumers', families, health professionals and service providers. *Australian Occupational Therapy Journal*, *63*(6), 439–440. https://doi.org/10.1111/1440-1630.12323

Hayes, A. F. (2017). *Introduction to Mediation, Moderation, and Conditional Process Analysis* (2nd ed.). Guilford Press.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A New Criterion for Assessing Discriminant Validity in Variance-based Structural Equation Modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Higgins, E. T. (1997). Beyond pleasure and pain. *American Psychologist*, *52*(12), 1280–1300. https://doi.org/10.1037/0003-066X.52.12.1280

Hofstede, G. (1993). Cultural constraints in management theories. *Academy of Management Perspectives*, *7*(1), 81–94. https://doi.org/10.5465/ame.1993.9409142061

Hohenberger, C., Spörrle, M., & Welpe, I. M. (2016). How and why do men and women differ in their willingness to use automated cars? The influence of emotions across different age groups. *Transportation Research Part A: Policy and Practice*, *94*, 374–385. https://doi.org/10.1016/j.tra.2016.09.022

Hong, W., & Thong, J. Y. (2013). Internet Privacy Concerns: An Integrated Conceptualization and Four Empirical Studies. *MIS Quarterly*, *37*(1), 275–298.

Hubert, M., Blut, M., Brock, C., Zhang, R. W., Koch, V., & Riedl, R. (2019). The influence of acceptance and adoption drivers on smart home usage. *European Journal of Marketing*, *53*(6), 1073–1098. https://doi.org/10.1108/EJM-12-2016-0794

IoT World Today. (2019). *Why the Smart Home Market Needs a 'Killer App.'* https://www.iotworldtoday.com/2019/11/25/why-the-smart-home-market-needs-a-killer-app/

Ji, W., & Chan, E. H. W. (2020). Between users, functions, and evaluations: Exploring the social acceptance of smart energy homes in China. *Energy Research & Social Science*, *69*, 101637. https://doi.org/10.1016/j.erss.2020.101637

Kappos, A., & Rivard, S. (2008). A Three-Perspective Model of Culture, Information Systems, and Their Development and Use. *MIS Quarterly*, *32*(3), 601. https://doi.org/10.2307/25148858

Katz, E., Blumler, J. G., & Gurevitch, M. (1973). Uses and Gratifications Research. *Public Opinion Quarterly*, *37*(4), 509. https://doi.org/10.1086/268109

Kim, J. Y., Chung, N., & Ahn, K. M. (2014). Why people use social networking services in Korea. *Information Development*, *30*(3), 276–287. https://doi.org/10.1177/0266666913489894

Kim, K. J., & Sundar, S. S. (2014). Does Screen Size Matter for Smartphones? Utilitarian and Hedonic Effects of Screen Size on Smartphone Adoption. *Cyberpsychology, Behavior, and Social Networking*, *17*(7), 466–473. https://doi.org/10.1089/cyber.2013.0492

Kim, M. J., Lee, C.-K., & Preis, M. W. (2020). The impact of innovation and gratification on authentic experience, subjective well-being, and behavioral intention in tourism virtual reality: The moderating role of technology readiness. *Telematics and Informatics*, *49*, 101349. https://doi.org/10.1016/j.tele.2020.101349

Kim, Y., Park, Y., & Choi, J. (2017). A study on the adoption of IoT smart home service: using Value-based Adoption Model. *Total Quality Management & Business Excellence*, *28*(9–10), 1149–1165. https://doi.org/10.1080/14783363.2017.1310708

Klobas, J. E., McGill, T., & Wang, X. (2019). How perceived security risk affects intention to use smart home devices: A reasoned action explanation. *Computers & Security*, *87*, 101571. https://doi.org/10.1016/j.cose.2019.101571

Koopman, P., & Wagner, M. (2017). Autonomous Vehicle Safety: An Interdisciplinary Challenge. *IEEE Intelligent Transportation Systems Magazine*, *9*(1), 90–96. https://doi.org/10.1109/MITS.2016.2583491

Krebs, P., & Duncan, D. T. (2015). Health App Use Among US Mobile Phone Owners: A National Survey. *JMIR MHealth and UHealth*, *3*(4), e101. https://doi.org/10.2196/mhealth.4924

Lancelot Miltgen, C., Popović, A., & Oliveira, T. (2013). Determinants of end-user acceptance of biometrics: Integrating the "Big 3" of technology acceptance with privacy context. *Decision Support Systems*, *56*, 103–114. https://doi.org/10.1016/j.dss.2013.05.010

Lankton, N., McKnight, D. H., & Tripp, J. (2015). Technology, Humanness, and Trust: Rethinking Trust in Technology. *Journal of the Association for Information Systems*, *16*(10), 880–918. https://doi.org/10.17705/1jais.00411

Laukkanen, T. (2016). Consumer adoption versus rejection decisions in seemingly similar service innovations: The case of the Internet and mobile banking. *Journal of Business Research*, *69*(7), 2432–2439. https://doi.org/10.1016/j.jbusres.2016.01.013

Lijarcio, I., Useche, S. A., Llamazares, J., & Montoro, L. (2019). Perceived benefits and constraints in vehicle automation: Data to assess the relationship between driver's features and their attitudes towards autonomous vehicles. *Data in Brief*, *27*, 104662. https://doi.org/10.1016/j.dib.2019.104662

Lutz, C., Hoffmann, C. P., Bucher, E., & Fieseler, C. (2017). The Role of Privacy Concerns in the Sharing Economy. *Information, Communication & Society*. https://doi.org/10.1080/1369118X.2017.1339726

Malhotra, N. K., Kim, S. S., & Agarwal, J. (2004). Internet Users' Information Privacy Concerns (IUIPC): The Construct, the Scale, and a Causal Model. *Information Systems Research*, *15*(4), 336–355. https://doi.org/10.1287/isre.1040.0032

Marikyan, D., Papagiannidis, S., & Alamanos, E. (2019). A systematic review of the smart home literature: A user perspective. *Technological Forecasting and Social Change*, *138*, 139–154. https://doi.org/10.1016/j.techfore.2018.08.015

Markets and Markets. (2020). *European Smart Home Market with COVID-19 Impact Analysis by Product (Lighting Control, Security & Access Control, HVAC Control, Home Healthcare), Software & Services (Proactive, Behavioural), and Region - Global Forecast to 2025*. https://www.marketsandmarkets.com/Market-Reports/european-smart-homes-market-1290.html

Martin, K. D., & Murphy, P. E. (2017). The Role of Data Privacy in Marketing. *Journal of the Academy of Marketing Science*, *45*(2), 135–155. https://doi.org/10.1007/s11747-016-0495-4

McKinsey Global Institute. (2013). *Disruptive technologies: Advances that will transform life, business, and the global economy*. https://www.mckinsey.com/~/media/mckinsey/business functions/mckinsey digital/our insights/disruptive technologies/mgi_disruptive_technologies_full_report_may2013.ashx

McKnight, D. H., & Chervany, N. L. (2001). What Trust Means in E-Commerce Customer Relationships: An Interdisciplinary Conceptual Typology. *International Journal of Electronic Commerce*, *6*(2), 35–59. https://doi.org/10.1080/10864415.2001.11044235

Meyer-Waarden, L., & Cloarec, J. (2021). "Baby, you can drive my car": Psychological antecedents that drive consumers' adoption of AI-powered autonomous vehicles. *Technovation*, 102348. https://doi.org/10.1016/j.technovation.2021.102348

Mordor Intelligence. (2021). *Global Smart Homes Market: Growth, COVID-19 Impact, and Forecasts (2021-2026)*. https://www.mordorintelligence.com/industry-reports/global-smart-homes-market-industry

Morgan, R. M., & Hunt, S. D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, *58*(3), 20–38. https://doi.org/10.2307/1252308

Ostrom, A. L., Fotheringham, D., & Bitner, M. J. (2019). *Customer Acceptance of AI in Service Encounters: Understanding Antecedents and Consequences* (pp. 77–103). https://doi.org/10.1007/978-3-319-98512-1_5

Parasuraman, A., & Colby, C. L. (2015). An Updated and Streamlined Technology Readiness Index. *Journal of Service Research*, *18*(1), 59–74. https://doi.org/10.1177/1094670514539730

Parasuraman, R., & Riley, V. (1997). Humans and Automation: Use, Misuse, Disuse, Abuse. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *39*(2), 230–253. https://doi.org/10.1518/001872097778543886

Park, E., Cho, Y., Han, J., & Kwon, S. J. (2017). Comprehensive Approaches to User Acceptance of Internet of Things in a Smart Home Environment. *IEEE Internet of Things Journal*, *4*(6), 2342–2350. https://doi.org/10.1109/JIOT.2017.2750765

Pavlou, P. A. (2003). Consumer Acceptance of Electronic Commerce: Integrating Trust and Risk with the Technology Acceptance Model. *International Journal of Electronic Commerce*, *7*(3), 101–134.

Penmetsa, P., Adanu, E. K., Wood, D., Wang, T., & Jones, S. L. (2019). Perceptions and expectations of autonomous vehicles – A snapshot of vulnerable road user opinion. *Technological Forecasting and Social Change*, *143*, 9–13. https://doi.org/10.1016/j.techfore.2019.02.010

Percival, J., & Hanson, J. (2006). Big brother or brave new world? Telecare and its implications for older people's independence and social inclusion. *Critical Social Policy*, *26*(4), 888–909. https://doi.org/10.1177/0261018306068480

Roca, J. C., García, J. J., & de la Vega, J. J. (2009). The importance of perceived trust, security and privacy in online trading systems. *Information Management & Computer Security*, *17*(2), 96–113. https://doi.org/10.1108/09685220910963983

Rosseel, Y. (2012). lavaan: An R Package for Structural Equation Modeling. *Journal of Statistical Software*, *48*(2), 1–36.

Schill, M., Godefroit-Winkel, D., Diallo, M. F., & Barbarossa, C. (2019). Consumers' intentions to purchase smart home objects: Do environmental issues matter? *Ecological Economics*, *161*, 176–185. https://doi.org/10.1016/j.ecolecon.2019.03.028

Sirgy, M. J. (2012). *The Psychology of Quality of Life: Hedonic Well-Being, Life Satisfaction, and Eudaimonia*. Springer Science+Business Media B.V.

Slovic, P. (1987). Perception of Risk. *Science*, *236*(4799), 280–285. https://doi.org/10.1126/science.3563507

Srite, M., & Karahanna, E. (2006). The Role of Espoused National Cultural Values in Technology Acceptance. *MIS Quarterly*, *30*(3), 679. https://doi.org/10.2307/25148745

Statista. (2021). *Smart Home Report*. https://www.statista.com/outlook/dmo/smart-home/worldwide

To, P.-L., Liao, C., & Lin, T.-H. (2007). Shopping motivations on Internet: A study based on utilitarian and hedonic value. *Technovation*, *27*(12), 774–787. https://doi.org/10.1016/j.technovation.2007.01.001

Toschi, G. M., Campos, L. B., & Cugnasca, C. E. (2017). Home automation networks: A survey. *Computer Standards & Interfaces*, *50*, 42–54. https://doi.org/10.1016/j.csi.2016.08.008

United Nations. (2016). *The World's Cities in 2016*. https://www.un.org/en/development/desa/population/publications/pdf/urbanization/the_worlds_cities_in_2016_data_booklet.pdf

Van Brummelen, J., O'Brien, M., Gruyer, D., & Najjaran, H. (2018). Autonomous vehicle perception: The technology of today and tomorrow. *Transportation Research Part C: Emerging Technologies*, *89*, 384–406. https://doi.org/10.1016/j.trc.2018.02.012

Venkatesh, Morris, Davis, & Davis. (2003). User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425. https://doi.org/10.2307/30036540

Venkatesh, Thong, & Xu. (2012). Consumer Acceptance and Use of Information Technology: Extending the Unified Theory of Acceptance and Use of Technology. *MIS Quarterly*, *36*(1), 157. https://doi.org/10.2307/41410412

Venkatesh, V. (2021). Adoption and use of AI tools: a research agenda grounded in UTAUT. *Annals of Operations Research*. https://doi.org/10.1007/s10479-020-03918-9

Venkatesh, V., & Zhang, X. (2010). Unified Theory of Acceptance and Use of Technology: U.S. Vs. China. *Journal of Global Information Technology Management*, *13*(1), 5–27. https://doi.org/10.1080/1097198X.2010.10856507

Voss, K. E., Spangenberg, E. R., & Grohmann, B. (2003). Measuring the Hedonic and Utilitarian Dimensions of Consumer Attitude. *Journal of Marketing Research*, *40*(3), 310–320. https://doi.org/10.1509/jmkr.40.3.310.19238

Wang, X., McGill, T. J., & Klobas, J. E. (2020). I Want It Anyway: Consumer Perceptions of Smart Home Devices. *Journal of Computer Information Systems*, *60*(5), 437–447. https://doi.org/10.1080/08874417.2018.1528486

Wilson, C., Hargreaves, T., & Hauxwell-Baldwin, R. (2017). Benefits and risks of smart home technologies. *Energy Policy*, *103*, 72–83. https://doi.org/10.1016/j.enpol.2016.12.047

Wirtz, J., Patterson, P. G., Kunz, W. H., Gruber, T., Lu, V. N., Paluch, S., & Martins, A. (2018). Brave new world: service robots in the frontline. *Journal of Service Management*, *29*(5), 907–931. https://doi.org/10.1108/JOSM-04-2018-0119

Wu, C.-L., Liao, C.-F., & Fu, L.-C. (2007). Service-Oriented Smart-Home Architecture Based on OSGi and Mobile-Agent Technology. *IEEE Transactions on Systems, Man and Cybernetics, Part C (Applications and Reviews)*, *37*(2), 193–205. https://doi.org/10.1109/TSMCC.2006.886997

Yang, F., & Xu, J. (2018). Privacy concerns in China's smart city campaign: The deficit of China's Cybersecurity Law. *Asia & the Pacific Policy Studies*, *5*(3), 533–543. https://doi.org/10.1002/app5.246

Yang, H., Lee, H., & Zo, H. (2017). User acceptance of smart home services: an extension of the theory of planned behavior. *Industrial Management & Data Systems*, *117*(1), 68–89. https://doi.org/10.1108/IMDS-01-2016-0017

Yang, H., Lee, W., & Lee, H. (2018). IoT Smart Home Adoption: The Importance of Proper Level Automation. *Journal of Sensors*, *2018*, 1–11. https://doi.org/10.1155/2018/6464036

Young, M. S., & Stanton, N. A. (2007). Back to the future: Brake reaction times for manual and automated vehicles. *Ergonomics*, *50*(1), 46–58. https://doi.org/10.1080/00140130600980789

Zhong, J. Y., & Mitchell, V.-W. (2012). Does Consumer Well-Being Affect Hedonic Consumption? *Psychology & Marketing*, *29*(8), 583–594. https://doi.org/10.1002/mar.20545

## Appendix A: PROCESS syntax

| Purpose | Ind. var. | PROCESS Syntax |
|---|---|---|
| **Model estimation + mediation analysis** | **EE** | process y=BI/m=PE SWB/cov=T Age Gender IoT Student Employ Worker Manage Unemploy SelfEmp Craft/x=EE/conf=95/bmatrix=1, 1, 1, 0, 1, 1/cmatrix=0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1. |
| | **PC** | process y=BI/m=T SWB/cov=PTS EE PE Age Gender IoT Student Employ Worker Manage Unemploy SelfEmp Craft/x=PC/conf=95/bmatrix=1, 0, 1, 0, 1, 1/cmatrix=1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1. |
| | **PTS** | process y=BI/m=T SWB/cov=PC EE PE Age Gender IoT Student Employ Worker Manage Unemploy SelfEmp Craft/x=PTS/conf=95/bmatrix=1, 0, 1, 0, 1, 1/cmatrix=1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1. |
| **Moderation analysis** | **EE** | process y=BI/m=PE SWB/cov=T Age Gender IoT Student Employ Worker Manage Unemploy SelfEmp Craft/x=EE/w=Country/mcw=1/conf=95/bmatrix=1, 1, 1, 0, 1, 1/cmatrix=0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1/wmatrix=1, 1, 1, 0, 1, 1. |
| | **PC** | process y=BI/m=T SWB/cov=PTS EE PE Age Gender IoT Student Employ Worker Manage Unemploy SelfEmp Craft/w=Country/mcw=1/x=PC/conf=95/bmatrix=1, 0, 1, 0, 1, 1/cmatrix=1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1/wmatrix=1, 0, 1, 0, 1, 1. |
| | **PTS** | process y=BI/m=T SWB/cov=PC EE PE Age Gender IoT Student Employ Worker Manage Unemploy SelfEmp Craft/w=Country/mcw=1/x=PTS/conf=95/bmatrix=1,0,1,0,1,1/cmatrix=1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 0, 0, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1, 1/wmatrix=1, 0, 1, 0, 1, 1. |