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ESSAYS ON THE CHANGING RISK LANDSCAPE IN SMART HOMES AND THE POTENTIAL FOR RISK PREVENTION

Iten Raphael

Iten Raphael, 2024, ESSAYS ON THE CHANGING RISK LANDSCAPE IN SMART HOMES AND THE POTENTIAL FOR RISK PREVENTION

Originally published at : Thesis, University of Lausanne
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FACULTÉ DES HAUTES ÉTUDES COMMERCIALES

DÉPARTEMENT DE SCIENCES ACTUARIELLES

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RISK PREVENTION**

THÈSE DE DOCTORAT

présentée à la

Faculté des Hautes Études Commerciales
de l'Université de Lausanne

pour l'obtention du grade de

Doctorat en sciences actuarielles

par

Raphael Sandro ITEN

Directeur de thèse
Prof. Joël Wagner

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Prof. Angela Zeier Röschmann

Jury
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Prof. Séverine Arnold, experte interne
Prof. Alexander Braun, expert externe

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Essays on the Changing Risk Landscape in Smart Homes and the Potential for Risk Prevention

sans se prononcer sur les opinions exprimées dans cette thèse.

Lausanne, le 12.06.2024

Professeure Marianne Schmid Mast, Doyenne



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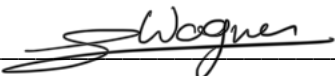
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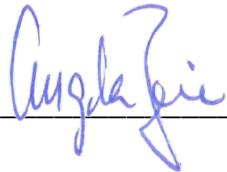
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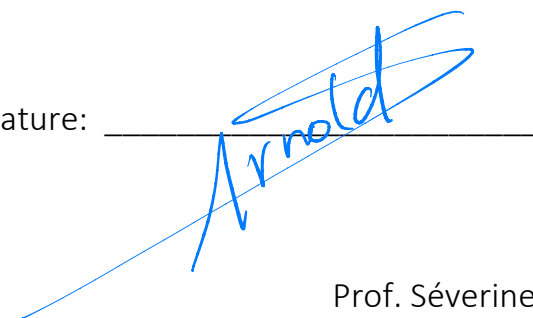
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Acknowledgements

The lasting impact we have is through our connection to other human beings: through friendship, parenting, mentorship, friendly competition, collaboration, and love.

– Lex Fridman, 2023

Firstly, I would like to thank Angela and Joël for making this thesis possible. I'm grateful for the fruitful collaboration and the unique format of our work together. Your trust, the opportunities you provided, and the encouragement have been invaluable. Most importantly, I have learned so much from both of you, and your interested, effective, clear, and consistently high-standard approach to work will continue to benefit me immensely.

I am also thankful for the many wonderful acquaintances, diverse perspectives, and multifaceted support I have received throughout this PhD journey. I am especially happy that some of these acquaintances have turned into real friendships, particularly at the ABF of the ZHAW School of Management and Law and the DSA of HEC Lausanne.

To my closest circle, your positive energy has significantly contributed to this milestone. And most importantly, to my family, who have been my greatest fans, my anchors, and my enablers throughout my academic journey. Words cannot express how thankful I am for all this and more. Thank you for your love and unconditional support.

Summary

This thesis comprises four essays investigating the influence of smart home technologies on household risks, insurance, and user perception. The focus is on identifying technology-enabled opportunities for risk prevention and insurance, as well as the dynamics that lead to their adoption. The first essay describes the changing risk landscape in smart home households by identifying and analyzing the associated risks. We provide a systematic review of the literature on emerging and pre-existing risks in smart home households, as well as the various methods mentioned and applied in the literature to evaluate and treat household risks. The second essay develops a survey data set that explores the motivations for using smart home technology for risk prevention. The data set includes 2490 individuals residing in Switzerland. It covers previously unexamined elements such as risk and insurance considerations, social dimensions, and parameters related to active and healthy aging, in addition to established adoption factors and user characteristics. Two additional contributions are derived from this data set. The third essay validates the preventive value of smart homes by investigating the influence of specific preventive services in the areas of safety and health on the expectation of performance and the intention to use smart home technologies. We quantify the strength of these relationships using a structural equation model and compare them with well-known non-prevention services related to comfort. The last essay focuses on factors that drive insurance demand in the context of smart homes. Employing econometric and machine learning methods, we identify factors that positively relate to insurance take-up. Specifically, we examine the influence of established factors from the non-life insurance demand literature and the impact of technology adoption drivers from the acceptance literature.

Résumé

Cette thèse est composée de quatre essais étudiant l'influence des technologies "smart home" sur les risques domestiques, l'assurance et la perception de ses utilisateurs. L'accent est mis sur l'identification des opportunités technologiques pour la prévention des risques et l'assurance, ainsi que sur les dynamiques qui conduisent à leur adoption. Le premier essai présente l'évolution des risques dans les maisons intelligentes et analyse les risques associés. Nous présentons une revue systématique de la littérature sur les risques émergents et préexistants dans ces maisons, de même que les diverses méthodes appliquées dans la littérature pour évaluer les risques domestiques. Le deuxième essai propose un ensemble de données d'enquête permettant d'explorer les motivations d'utilisation des smart home technologies pour la prévention des risques. L'ensemble des données comprend 2490 personnes résidant en Suisse. Il contient des éléments qui n'avaient pas été étudiés auparavant, tels que les risques et les considérations d'assurance, les dimensions sociales et les paramètres liés au vieillissement actif et en bonne santé, en plus des facteurs d'adoption et des caractéristiques des utilisateurs. Cette série de données engendre deux contributions supplémentaires. Le troisième essai valide les valeurs préventives des maisons intelligentes enquêtant sur l'influence de services préventifs des domaines de la sécurité et de la santé sur les performances attendues et sur l'intention d'utiliser les technologies. Nous quantifions la force de ces relations avec un modèle d'équations structurelles et les comparons à des services non préventifs bien connus liés au confort. Le dernier essai porte sur les facteurs qui déterminent la demande d'assurance dans le contexte de la domotique. Grâce à des méthodes économétriques et de machine learning, nous identifions les facteurs associés positivement à l'intérêt pour une assurance "smart home". Plus précisément, nous examinons l'influence des facteurs établis dans la littérature sur la demande d'assurance non-vie et l'impact des facteurs d'adoption de la technologie dans la littérature sur l'acceptation.

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Chapter 1

Introduction

By the end of 2023, more than one million Swiss households were considered “smart homes.” These homes feature water leak detectors to monitor changes in water pressure, smoke detectors for fire detection, and motion sensors for activity tracking. The development of these products has been facilitated by the reduction in production costs (Microsoft, 2019, see Figure 1.1), which is also related to the maturity of these applications and their adoption rates (Statista, 2023, see Figure 1.2). Smart homes offer new opportunities to reduce existing risks at home and contribute thereby to risk prevention and better risk management practices. As the relationship between technology and risk continues to evolve, this potential raises new questions for key players in the field, including users and insurers.

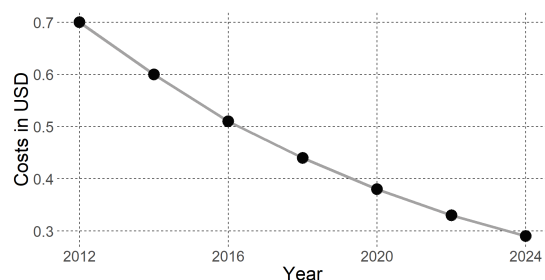


Figure 1.1: Average manufacturing cost of IoT sensor (Microsoft, 2019).

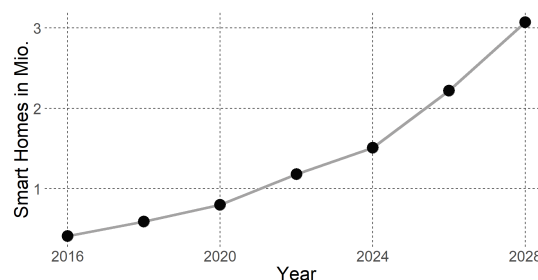


Figure 1.2: Number of smart homes in Switzerland (Statista, 2023).

Note: IoT costs for 2020–2024 and smart home estimates for 2024–2028 reflect respective year-of-report estimates.

Research questions and scope

This thesis aims to describe the changing risk landscape of smart homes and, in particular, to provide a better understanding of user preferences in the adoption of smart home technology for risk prevention. We build on similar work that highlights the potential of technology-enabled prevention services to proactively mitigate risk and enable innovative business models focused on enhanced risk management (Flückiger and Carbone, 2021). Examining the evolving risk landscape and its potential reveals several issues. It is crucial to identify the major changes in the risk landscape, areas where risks can be reduced, and emerging risks. The risk perception of inhabitants and their behavior significantly influence this landscape (Jacobsson et al., 2016). It is further affected by differences in risk perception between individuals and experts, as well as the expected shift in risk costs from individual risk to systemic consequences (Park et al., 2018). With a better understanding of the changing risk landscape, current issues related to risk pre-

vention offerings can be addressed. Understanding changes in customer behavior is thereby crucial. Although individuals may recognize the preventive benefits of such services, it does not necessarily translate into usage (Shank et al., 2021). Other factors, such as the usability of technology, enjoyment, social influences, and specific personality traits, contribute to this multifaceted dynamic (Hubert et al., 2019). Insights into the influential factors that affect customer behavior can provide actionable information for various stakeholders from practice, particularly insurance companies. Given that technology-based prevention applications can be identified in other lines of insurance, it is worth considering the extent to which data-driven insurance solutions will emerge in the smart home. Insurers still face challenges in delivering these products despite their expertise in using technology to assess and mitigate risk and repeated attempts to offer smart home insurance products (Flückiger and Carbone, 2021). To effectively leverage the potential of IoT and keep up with advancements in telematics and wearables (Saliba et al., 2022; Ziakopoulos et al., 2022), they are working towards a better understanding of policyholders' evolving expectations.

Smart home technologies refer to various Internet of Things (IoT) devices and services that transform a living space into a remotely manageable, digitized, and automated environment (Marikyan et al., 2019). The key applications of the prevention services are energy, health, and safety. Smart home energy services aim to reduce energy consumption through continuous monitoring and automation, contributing to sustainability efforts by optimizing energy usage (Große-Kreul, 2022). Health services target individual well-being. The majority focus on the needs of older adults or those with disabilities, promoting healthier and more independent living (Tural et al., 2021). Safety services enable residents to enhance home security, prevent accidents, and reduce financial losses (Blythe and Johnson, 2019). For instance, sensors can be installed on water pipes to monitor consumption patterns and detect unusual changes over time or within a specific area. This can trigger alerts or actions to prevent potential water damage, significantly reducing the frequency and severity of losses as a consequence of water pipe bursts (Davis, 2020).

In summary, this work examines the evolving risk landscape of smart homes and user preferences for adopting smart home technology to prevent risks. A risk is thereby considered a condition that may cause an adverse deviation from the expected or desired results. We focus on risks faced by private households, including traditional risks such as fire and theft, as well as modern challenges like cyber threats and privacy concerns. As technology becomes more prevalent in homes, it creates new uncertainties and changes the risk landscape. However, it also provides new opportunities for risk management. Insurance has traditionally played an important role in mitigating the financial consequences of household risks by transferring them to third parties. As such, it is expected to be affected by this dynamic.

Synthesis of the thesis articles

This thesis consists of four interlinked essays. They provide insights into the evolving risk landscape of smart households, the dynamics that lead to technology adoption, the value of prevention for smart home users, and the implications for insurance offerings based on this technology. An overview of the research is presented in Figure 1.3.

Chapter 2. The second chapter of this thesis systematically analyzes the effects of smart home technology on the risk landscape of private households. As smart homes have great

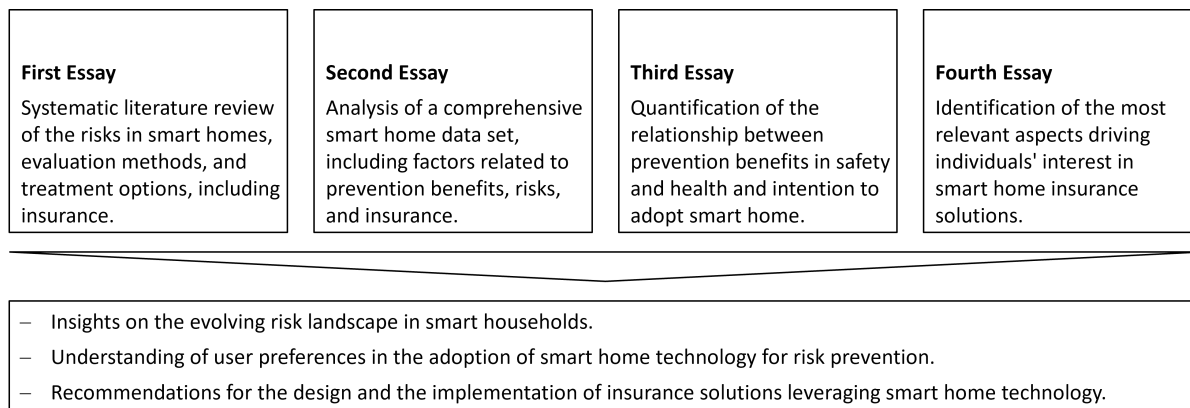


Figure 1.3: Synopsis of the four essays of this thesis and expected outcomes.

potential for risk management but simultaneously create new risks, it is crucial to understand the risks associated with them to provide a basis for assessing their potential. Following the PRISMA reporting guidelines, we conducted a systematic literature review and selected 59 references for the final analysis. We summarize emerging and pre-existing risks and indicate the influence of smart homes on each risk, where available. The risks highly impacted by smart homes and extensively studied are those associated with cyber security, privacy, and dependence. The review also identifies various methods used by academic researchers and practitioners to evaluate household risks. Most risk evaluation methods mentioned in the literature come from the information security or acceptance research disciplines, indicating that these two disciplines primarily drive the research. The findings originate from a technical perspective, or the risk is evaluated solely by its perceived impact on technology adoption. Additionally, we present the risk treatment options that aim to primarily reduce cyber risks. These options include initiatives to increase awareness, disseminate knowledge, and empower users.

Chapter 3. After presenting the evolving risk landscape of smart homes, we develop a comprehensive data set on smart home adoption with a focus on prevention benefits, risks, and insurance. By analyzing 1 515 participants, we provide an overview of the factors contributing to smart home adoption. In addition, regressions were conducted to analyze previously unstudied factors related to the technology's benefits and the user's characteristics. Our findings indicate that safety benefits are recognized and welcomed by potential users, suggesting they could be a door opener to the topic. Additionally, health-related benefits are positively linked to an individual's willingness to adopt smart home technology. The chapter also reveals previously unstudied characteristics of interested individuals related to active, healthy aging. We show that the prevention premise of smart homes is well-suited for socially engaged older individuals, suggesting a possible relationship between interest in smart homes and an active, healthy lifestyle. Additionally, we confirm the significance of user characteristics, such as knowledge, technology and risk affinity, gender, and other established factors from the literature on smart home adoption, including social influences from peers and hedonic motivators.

Chapter 4. The previous chapter concluded by hypothesizing the value of smart home technology to prevent safety and health risks. This chapter sets the stage for investigating how the premise of prevention can increase interest in smart homes. Given that current research and practice focus on comfort benefits, we developed a structural equation model to analyze the hy-

pothesized effects of preventive benefits and broader considerations of comfort while controlling for personality traits. Using the data set described in the previous chapter, we combine the method of partial least squares with a stepwise selection procedure to explain critical relationships within the model and extract the relevant set of personality traits. We find that preventive health and safety benefits have a significant relationship with higher interest in smart homes, while comfort benefits remain more important. Based on these findings, we conclude that a value proposition emphasizing safety and health benefits must be well contextualized within the broader range of user comfort and performance expectations. Personal characteristics related to technology, sociodemographics, and an active aging lifestyle also play a significant role in shaping interest. These findings could be helpful for stakeholders who are interested in leveraging smart home technology for risk management purposes.

Chapter 5. The final chapter of this thesis identifies the factors that drive the adoption of smart home insurance solutions. Our analysis utilizes the aforementioned data set and applies both econometric and machine learning techniques. Initially, a stepwise selection algorithm based on logistic regression is used to identify the most significant variables from a set of 65 potential predictors. Using a log-likelihood ratio test, the retained variables are then ranked based on their importance. A random forest model is also used to conduct recursive feature elimination and cross-validate the retained variables and their importance rankings. The results indicate that the most relevant factors are associated with the costs and incentives of smart home insurance. We also demonstrate that an individual’s willingness to share data with the insurer is essential. Additionally, insurers should provide services aimed at reducing risks in the home, which is another factor that greatly increases interest in smart home insurance. In light of these results, we suggest considering new drivers beyond traditional insurance demand or technology acceptance when incorporating smart home technologies into home insurance.

Position on the topic with future prospects in mind

This thesis explores the impact of smart home technologies on the risk landscape in private households and how individuals perceive these technologies and associated risks. It validates the value of prevention in specific smart home service areas and identifies the factors that influence the adoption of such technology-based prevention services, including insurance. The findings have important implications for households’ individual risk management as they offer insights into risk perception, risk mitigation behavior, and risk pricing for smart homes. Additionally, these results are relevant to insurance practitioners, as they relate to the fundamental function of insurance, which involves exchanging an uncertain loss for a small loss (the premium). Smart home insurance provides insurers with additional information that can be used to better estimate, control, and proactively reduce the uncertainty attributed to losses. This comes with new expectations from policyholders who expect insurers to offer a value proposition beyond traditional financial compensation.

We may venture into the future based on the evidence discussed in this thesis. The importance individuals place on their homes is growing. This trend is fueled by the increasing desire of older adults to age in place and has been further amplified by the COVID-19 pandemic and its aftermath. The home has become a sanctuary for personal well-being and a vital workspace. Technological solutions designed for these purposes will continue to advance, particularly as they become more affordable, user-friendly, and safe. Drawing parallels to other IoT applica-

tions, such as wearable technologies, can help discuss future perspectives. Wearables were once viewed as gadgets that monetized health benefits through daily step counts but with significant privacy concerns, particularly in the context of health insurance. Today, activity trackers and smartwatches are widely available at low costs. Various preventive features are offered, and their benefits convince users to share data across technology companies, sports apps, health organizations, and even gaming platforms. Although the future relevance of the underlying technology seems assured, leveraging business models aimed at the prevention premise of smart homes is less straightforward. As significant stakeholders in the field, insurers have the opportunity to transform their business practices from primarily being risk financiers to comprehensive risk management service providers. This transformation can potentially improve the relationship between policyholders and insurance companies. However, it requires both parties to align on the expected benefits of smart home technology and the associated risk management efforts and share the costs of these activities.

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Chapter 2

On the Identification, Evaluation and Treatment of Risks in Smart Homes: A Systematic Literature Review

The emergence of smart technologies in homes comes with various services and functions for everyday life. While a smart home (SH) is associated with great potential in terms of comfort and risk treatment, it also introduces new and alters existing risks. Despite a growing number of academic studies on SH risks, research is fragmented with regard to its focus on certain disciplines and is still rather technology-focused. In this paper, we fill this gap by providing a comprehensive understanding of relevant risks through a systematic literature review. Following the guidelines of the PRISMA reporting protocol, we search 1196 academic and practitioners' publications related to household risks or risk perceptions of SH users. A final set of 59 records results in three main themes. They include (1) a synthesis of pre-existing and emerging risks sketching the new risk landscape of SH households, (2) a discussion of the prevailing risk evaluation methods, and (3) a presentation of SH-related risk treatment options with a particular emphasis on insurance. We specify the influence of SH on risks and risk perception, and highlight the relevance of analyzing the interconnection of risks in complex systems, such as SH. Our review lays the basis for assessing SH risks and for enabling more comprehensive and effective risk management optimization.

Note: This is a joint work with J. Wagner and A. Zeier Röschmann, published in *Risks* (2021), volume 9, number 113. The authors would like to thank the participants of the ISFA Lyon and DSA-HEC Lausanne Seminar (2021) for their feedback on previous versions of this manuscript.

2.1 Introduction

Increasing households' inclusiveness, safety, resilience, and sustainability is a global trend supported by the emergence of new technologies (Salhi et al., 2019). Smart technologies and services also facilitate the integration of work life into the private home, a trend that has been amplified by the surge in momentum brought by the COVID-19 pandemic (Von Gaudecker et al., 2020). A smart home (SH) can address needs as energy management (Reinisch et al., 2011; Scott, 2007), health (Alam et al., 2012; Ehrenhard et al., 2014), security (Blythe and Johnson, 2019; Schiefer, 2015), lifestyle, and convenience (Chan et al., 2012) through the use of connected and embedded devices. Early definitions by Lutolf (1992), and later Aldrich (2006), discuss the essence of SH in a capacious manner. They capture the technical dimension, the services and functions that SHs provide, and the types of user needs that the technologies are designed to meet. Today, two types of SH definitions are used: one that refers to the technological attributes and another that characterizes the service perspective (Sovacool and Furszyfer Del Rio, 2020). However, Marikyan et al. (2019) show that both types of definitions address three typical attributes of SH, namely the technological aspects regarding hardware and software, the services enabled by SH, and, thus, the ability to satisfy certain household needs. In this research, we consider SH as a home equipped with a set of smart technologies that offer remote, digitalized, and automated services to a resident improving its quality of home life.

As homes become "smarter", our way of living changes accordingly (Keller et al., 2018). As such, the risks associated with a household change fundamentally. SH is associated with great potential in terms of risk treatment, but, at the same time, causes new risks (Denning et al., 2013). In fact, new risks, especially in the area of cyber security and privacy, emerge and have been discussed in recent literature (Loi et al., 2017). Thereby, human-related or software-related risk sources, e.g., inadequate access control, are identified as crucial (Jacobsson et al., 2016). While much attention is given to privacy and cyber security risks, other household risks, such as water, fire, or theft, have attracted little academic attention in SH settings so far. Practitioners' studies, however, promote SH as an important risk mitigation measure. For example, a study by Davis (2020b) show that the risk of water damage could be significantly reduced with the implementation of SH. To date, there are no systematic reviews of the literature on risks in SH. Various reviews following more narrow approaches exist. For example, Amiribesheli et al. (2015) summarize the state of affairs from a health perspective, Hosseini et al. (2017) take the viewpoint of energy management services and Marikyan et al. (2019) conduct a use-case overarching user-centered analysis. In addition to some purely technical analyses of cyber risks (Ali et al., 2019; Nawir et al., 2016), the study by Blythe and Johnson (2019) synthesizes the literature on crimes facilitated by Internet of Things (IoT) environments, with a particular emphasis on the home environment.

Hence, despite a growing number of academic studies on SH and the associated risks, research is fragmented in that it focuses on selected risks or risk perception in the context of SH acceptance. As such risks are mainly analyzed from information security or technology acceptance disciplines, separately and predominantly field-specific but have not yet been systematically synthesized. As a consequence, the literature on risks in SH lacks a comprehensive picture about which risks emerge or change with SH dynamics.

In this systematic literature review, we identify and analyze the risks that are associated with SH households. By adopting an interdisciplinary approach, we aim to improve the understanding of the (changing) risk exposure of SHs. A more comprehensive understanding of risks and their drivers lays the basis for the optimization of risk management. This also enables future research to propose measures that effectively address risks in their entirety and thereby generate value out of SH from a risk management perspective.

From an initial collection of 1 196 academic and practitioners' publications, we retain 59 references that we include in our systematic literature review. The study of the final corpus resulted in three main themes of SH risk research. First, we identify pre-existing and emerging risks in SH on the basis of an inductive categorization. Emerging risks related to cyber and dependency are the most prominent in the literature. In the case of pre-existing risks, the extant literature mainly focuses on financial aspects or household risks known from the insurance business. Second, we present applied risk evaluation methods, most of which are methods from the information security discipline or from acceptance research. In addition, risks are evaluated using well-known frameworks (e.g., ISO 31000). Third, we structure risk treatment options in two groups. Those that are recommendations for SH technology and service providers and those representing options for end-users. Implications for the insurance industry are studied hereunder.

The paper is organized as follows. In Section 2.2, we present the methodology used to review the literature and to derive the corpus of records that we analyze. We present our findings on the risk identification in SHs and our synthesis on pre-existing and emerging risks in Section 2.3. In Section 2.4, we discuss the prevailing risk evaluation methods. Finally, we present the identified risk treatment options in Section 2.5. Thereby, we put special emphasis on the risk transfer to insurance in the SH context. We conclude in Section 2.6. In the Appendix, we provide a comprehensive synopsis of the reviewed papers (Tables 2.3 and 2.4), as well as a detailed overview of the identified risks (Table 2.5).

2.2 Methodology

In this section, we present the review strategy and descriptive statistics on the retained body of literature. Finally, we synthesize the final corpus by presenting the main themes and by introducing the underlying theoretical concepts and terminology.

2.2.1 Review strategy and data collection

Our review identifies and summarizes risks in SHs, using a systematic methodological approach. To ensure a high degree of reliability, we follow Tranfield et al. (2003) and use the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol (Page et al., 2020) as a reporting guide.

Before starting the systematic review and to obtain an initial understanding of the topic, we conducted a preparatory literature review which included the identification of gaps in research, study objectives and development of a review protocol. This preparatory review has revealed several gaps that pointed to the need for a systematic investigation of risks in the context of SHs. It has also shown that beyond academic research, an increasing number of practitioners' studies

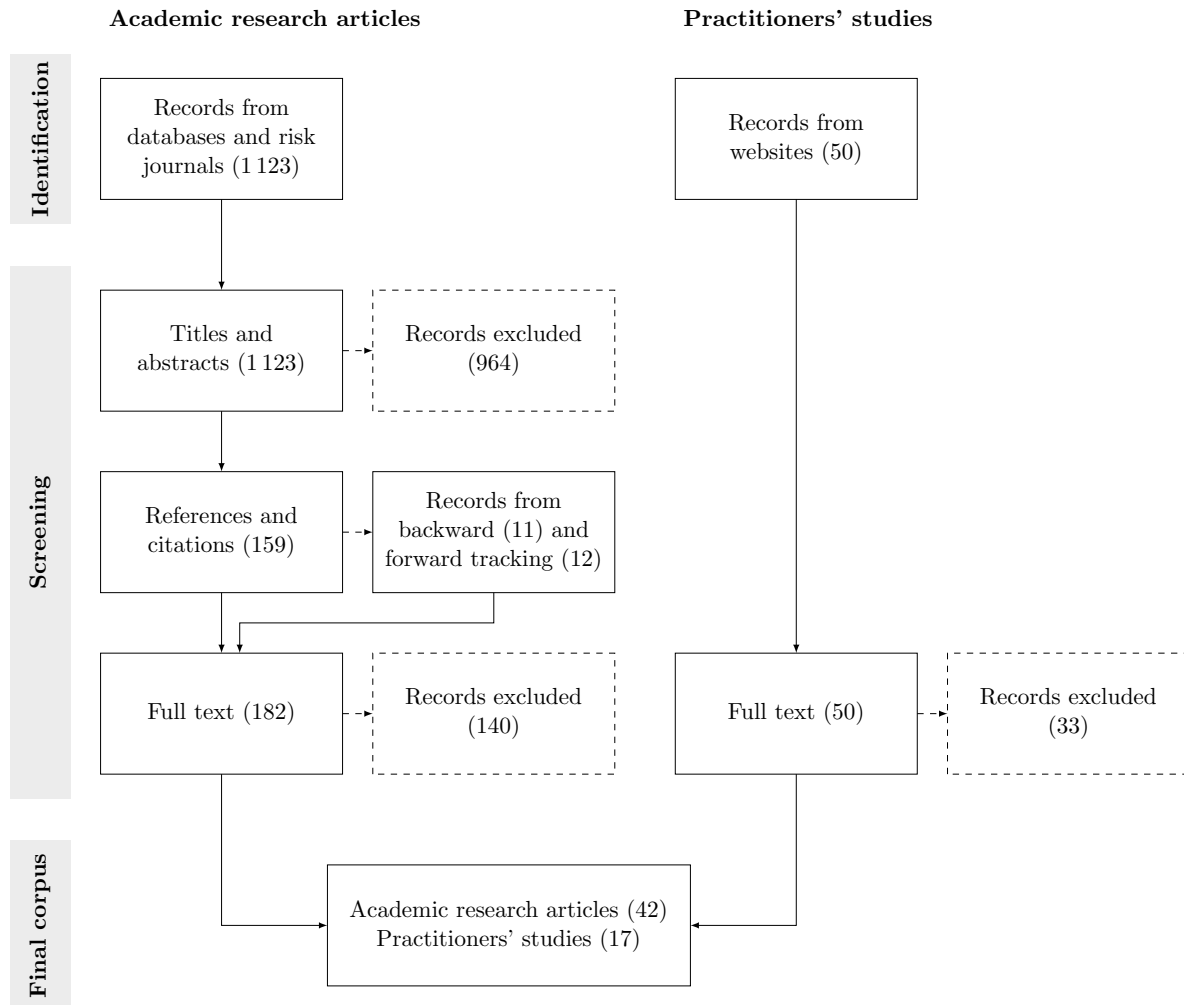


Figure 2.1: Flow diagram for the identification and screening of records along PRISMA guidelines.

point to relevant aspects regarding risks in SHs. For this reason, we organize our research in two streams (see Figure 2.1). In the first search stream, we focus on academic research articles. In the second search, we pinpoint relevant industry expertise, such as reports from risk management experts, government departments, or insurance companies. We view them as a relevant expert group, especially, since insurance companies, for example, have the most comprehensive data on household risks and possess distinct risk analysis skills.

For the academic search stream, we selected Web of Science, EbscoHost, and ProQuest as information sources, considering all citation indexes of the Web of Science Core Collection, only Business Source Premier in EbscoHost, and ABI/INFORM Global, as well as ABI/INFORM Trade and Industry, in ProQuest. To guarantee a holistic view of all risks that appear in SHs, we further identified 16 risk journals (e.g., Risk Management and Insurance Review or Asia-Pacific Journal of Risk and Insurance), which were not covered by the selected databases. We screened these journals using the same selection criteria. The choice of keywords focused on the terms “smart home” and “risk”.¹ We defined eligibility criteria in terms of time span (years

¹The full search streams used are as follows: *AB("smart home*" OR "connected home*" OR "smart living" OR "smart building*" OR "smart technology") AND AB("risk*" OR "threat*" OR "barrier*" OR "limit*")*, as well as *AB("iot" OR "internet of things" OR "big data") AND AB("risk*" OR "threat*" OR "limit*") AND*

from 2002 to 2020), language (English, German, French, and Italian), and included all types of sources since no prior work systematically covered risks in SHs. The data collection process was facilitated by the use of a reference manager software (Mendeley) and clear decision rules on the origin of the data. If two sources pointed to the same results, the primary dataset was collected. The final query in the databases and the risk journals was performed in July 2020 and resulted in 1 123 records.

Following the identification of the academic research articles, a screening process was conducted (see Figure 2.1). We used inclusion criteria coded on a scale ranging from 0 to 3 as follows: Level 3 is used when risks are analyzed in a systematic and holistic way in the source, level 2 indicates that risks are discussed but the focus is on a single risk (e.g., technological risk), level 1 denotes work wherein some aspects of risk management are mentioned, or where the context suggests that risks may be discussed, and level 0 indicates that no relevant aspects on risks are discussed. Further, we excluded studies focusing on medical aspects concerning certain disease risks (e.g., risk of a stroke in a home-care setting) or technical studies (e.g., household energy management) that do not discuss risks. While one of the authors handled the selection and scoping of the articles, the other authors acted as reviewers and conducted the proof-reading to validate the collection. Independence was guaranteed since no knowledge on the other reviewer’s scoring was shared. Disagreements were resolved afterwards by a look-up of the detailed results and, if necessary, by a discussion whether the study should be ranked up or down.² In the first step of screening, reviewers scored the studies based on the titles and the abstract, resulting in 159 references scored 1 or higher that were retained.

Based on these 159 records, a backward and forward citation search was performed. This led to 11 and 12 documents being added, respectively, from backward and forward tracking. A set of 182 records was considered for full-text assessment. After excluding 140 records that did not meet the SH inclusion criteria, 42 academic research articles ranked as relevant.

In the second search stream, we identified practitioner’s studies in the grey literature. A dedicated web search pursued a specific search strategy focusing exclusively on organizations engaged in household risks or SH technology. A total of 24 insurance companies and 63 other organizations were included in the search.³ We extracted the results of the top-ranked results for each organization and retained 50 references scoring 1 or higher. Full-text screening on these records resulted in the exclusion of 33 records and, finally, 17 practitioners’ studies are retained.

The final corpus of literature that we use in the sequel includes 59 records: 42 academic research articles and 17 practitioners’ studies. A synopsis of the records is provided in Tables 2.3 and 2.4 in Appendix 2.7. For each record, we provide the geographical scope (column “region”), type of publication (column “type”), and the research method used (column “method”), as well as

AB("home" OR "household*" OR "house*").*

²To limit any inappropriate use of the methodology and to counteract the risk of bias, the recommendations of Thomé et al. (2016) were followed. The review protocol and the inclusion criteria were jointly developed by the team of authors. We consequently sought to work with more than one independent reviewer and compared individual selections only after scoring was completed. Finally, for certainty assessment of the literature, we included several factors. One indicator was the degree to which additional search streams led to known results identified in a prior search stream. Dedicated search processes were done for grey literature to validate the existing knowledge and reveal new content. Moreover, we performed text mining on the final corpus of records to validate whether any relevant themes were not covered by the full-text articles.

³An example query for web search is as follows: *"smart home" AND "risk" site:lexisnexis.com.*

information on key contents and main results. Further, we identify the records related to risk identification (RI), risk evaluation (RE), and risk treatment methods (RT), including insurance.

2.2.2 Descriptive statistics

In the following, we provide descriptive statistics on the screened records and the final corpus of literature. We perform a frequency analysis on the records sought for full-text screening (182 research articles and 50 practitioners’ studies; see Figure 2.1) and text mining on the final body of records (42 articles and 17 studies). These analyses visualize key metrics of the literature and the results help to provide an initial mapping of the main concepts.

Frequency analysis of the screened records. Using the 182 academic research articles and the 50 practitioners’ studies retained for full-text screening, we perform a frequency analysis on the publication year of the records and on the geographical region under investigation. The graph in Figure 2.2a shows the development of the number of records between 2011 and 2020. It becomes evident that the relevant research field steadily grows. The number of publications in our database increased from 2 records in 2012 to 56 records in 2019. In the earlier 2000s, there are only sporadic occurrences with one or two records per year. We do not discuss the figure for 2020, as it is incomplete since the search covered publications until July 2020. We illustrate the geographical distribution of records in Figure 2.2b. The anglo-saxon region dominates the research activities, with the U.S. and UK contributing most, respectively, with 52 and 34 records. South Korea (KR, 19) and China (CN, 12) follow next. Overall, more publications originate from Europe (57) than Asia (47).

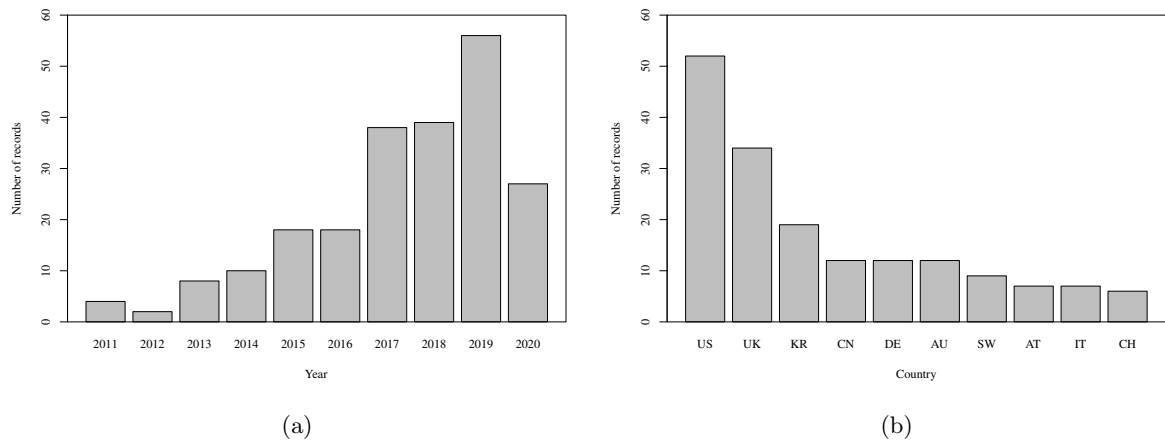


Figure 2.2: Frequency analysis of the screened records from 2011 to 2020 and per country. (a) Development over time. (b) Distribution by country. Note: For 2020, records include publications until July.

Text mining on the final body of records. Text mining on the main corpus of 42 research articles and 17 practitioners’ studies was used to quantitatively assess the concepts included in the body of literature. A visualization of the results is given in Figure 2.3.⁴ Expectedly, the

⁴The criteria for the scoring were English language, at least 3 letters and on the basis of a word stem (e.g., the key term “secur” includes among others the words “security” and “secure”).

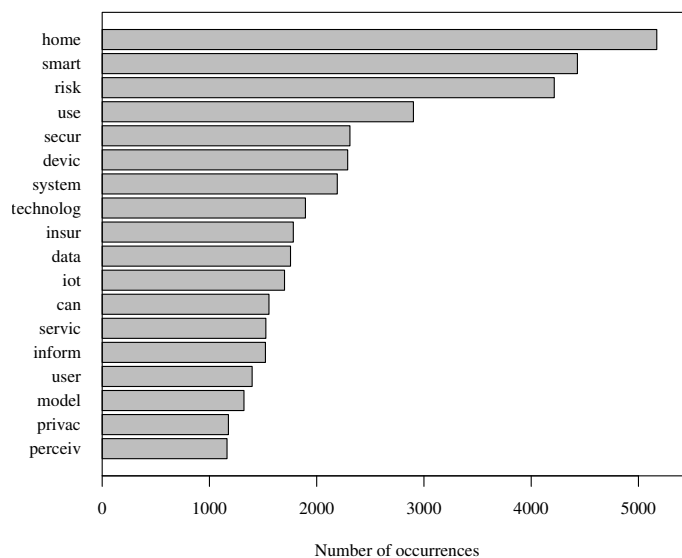


Figure 2.3: Text mining of key terms in the final corpus of records.

key terms “smart”, “home”, and “risk” are the most frequent since they were searched for to initially determine the records. An interesting finding is that “secur” appears far more often than “privac”. This reflects the relevance of security, which is of particular concern for the SH risk literature in terms of cyber security and physical security (see Section 2.3.1). The relatively high frequency of terms with “use”, especially compared to “technology”, is likewise of interest. It indicates that usage drives risks, yet research remains primarily technology-focused. Insurance-related research (“insur”) counts a relatively high number of hits when compared to the keys “servic”, “user”, or “perceiv”. This is mainly due to the range of insurance-related practitioners’ studies that resulted from the web search.

2.2.3 Data synthesis

To synthesize the data, we adopted an inductive thematic analysis method as defined by Braun and Clarke (2006). To minimize the risk of bias, we pursued a six-phase process where topics are coded with no pre-existing categorization within the research field (see, e.g., the orientation by Mikkonen and Kääriäinen (2020)). The value of an inductive thematic analysis for our research question relates to the capacity to analyze latent themes. Since there is no prior work reviewing risks in SH and we combine different disciplines analyzing risks separately, the chosen bottom-up approach leads to the best possible completeness. Our analysis results in three main themes, to which all risk relevant statements can be assigned. The relevant themes are the following:

- *Risk identification.* The difficulty of identifying risks for SHs resides in having different terminologies due to the diversity of disciplinary origins. We present our findings on risk in SHs in Section 2.3 and attempt to keep a simple structure. For this reason, we adopt the risk management framework ISO 31000 (ISO, International Organization for Standardization, 2018). That framework is generally applicable, simple to use and proven in the corporate context. We summarize the identified risks along their influence on impact and acceptance (see Table 2.1 in Section 2.3 and Table 2.5 in Appendix 2.7).

- *Risk evaluation.* Methods to assess risks can be found in different research areas. In Section 2.4, we present the risk evaluation methods available from the literature and attribute them to the respective disciplines. Findings from academic literature are synthesized together with the methods found in practitioners' studies (see Table 2.2 in Section 2.4).
- *Risk treatment and insurance.* Finally, selecting and implementing appropriate measures to address risks of SHs represents a nascent topic of SH risk research. However, the focus here is still entirely on cyber risks. Since we cannot fall back on any established concepts for structuring, the measures are divided into two categories. The first presents options that act as recommendations for SH providers. The second presents options for the users. The effect of SH on insurance, which represent a treatment option in their own right, is further discussed in depth.

While other topics, such as technology characteristics, benefits, adoption, sustainability, society, commercial, and legal, emerged, they are interesting for SH overall, but, since they are not relevant for our risk focus, we do not discuss them further. Both Tables 2.3 and 2.4 in Appendix 2.7 provide a synopsis of the final corpus of records and the association of the literature to the three main themes.

2.3 Risk identification

In general terms, a risk is a deviation from a desired condition (ISO, International Organization for Standardization, 2018). With the broad variety of technology available for home, likewise, various targets and various possible deviations arise (Nurse et al., 2016). This section presents the risks identified from the final corpus of 59 records. We summarize the risks along their influence on impact and acceptance. Furthermore, we structure our synthesis in emerging and pre-existing risks. On the one hand, pre-existing risks are considered as those already being discussed for households without SH devices or services. Often, they include risks from insurance-related studies. Emerging risks, on the other hand, refer to risks emerging with the integration of SH applications in a household. They are typically developing or changing risks that are more difficult to quantify (Mazri, 2017). Emerging risks to privacy and cyber security have been signaled early on by Radomirovic (2010).⁵ At the end of the section, we provide an overview of the risks that we discuss (see Table 2.1).

2.3.1 Emerging risks

The implementation and use of smart technologies in homes gives rise to emerging risks (Denning et al., 2013). In the literature, these emerging risks are studied in particular from the viewpoints of information security and technology acceptance. In the former, cyber risks and their technological treatment are examined, whereas in the latter, the focus is on societal risks that affect users to varying degrees.

⁵We observe that risk analyses from the information security literature often take a distinct approach in describing risks by identifying the asset, vulnerability and threat of a risk (Jacobsson et al., 2016). For such risks, we follow this structure. Similarly, risk analyses from the technology acceptance literature use a specific vocabulary. Given their user-centric orientation, the risks identified from this literature are described as perceived risks by lay users. As an example, perceived privacy risks relate to consumers' concern of having personal data misused or disclosed to third parties without their agreement (Kang and Kim, 2009). Thus, the focus is fully on the user's perception.

- *Privacy.* We find emerging cyber risks related to privacy and cyber security among the most relevant risks for SH (Loi et al., 2017). Privacy risks refer to the inappropriate handling of personal user data collected from SH (Gerber et al., 2019). As devices, like surveillance cameras or personal wearables, become part of the SH ecosystem, Jacobsson (2016), among others, names privacy risks as the most undesirable consequence. Sovacool and Furszyfer Del Rio (2020), for example, attributes the highest probability of occurrence to privacy risks, while Park et al. (2019) attribute the highest severity to it. In addition, Tanczer et al. (2018) sees the status of privacy as the most fundamental risk under the dynamics of SH. The authors further warn that privacy risks are most likely to be accepted on an individual level, thus creating long-term risks for society as a whole.

In research on the acceptance of SH technology and services, perceived privacy risks are extensively analyzed. Several studies state that privacy risks contribute the strongest to the users' overall risk perception (Marikyan et al., 2019). Interestingly, all studies agree that while privacy risks have a strong influence on risk perception, overall risk perception does not influence acceptance (Kim et al., 2017; Klobas et al., 2019; Wang et al., 2020). Hubert et al. (2019) shares the opinion but argue that perceived privacy risks remain significant in the context of adoption, as they have an indirect influence on other acceptance variables. Studies from Alaiad and Zhou (2017) and Wilson et al. (2017) also conclude that perceived privacy risks are not the most relevant factor for the overall risk perception. Park et al. (2018) categorizes the surveyed sample into three groups: low, moderate and high overall risk perceivers. For the low risk perceivers, privacy risks do not influence the overall risk perception, whereas for the modest and high risk perceivers, they have the largest influence. Lastly, the work of Hong et al. (2020) show no direct influence of perceived privacy risks, and thereby does not investigate the overall risk perception.

In our literature study, we found two unique approaches to perceived privacy risks. On the one hand, Lee (2020) analyzes how users perceive certain vulnerabilities. Vulnerabilities relating to user behavior are perceived as the most significant, technology vulnerabilities also result to be important, legal vulnerabilities are considered vaguely significant and provider vulnerabilities are not significant. On the other hand, Gerber et al. (2019) compares the significance of perceived privacy risk in the overall risk perception in SHs to the significance in social media and in smart health. Especially abstract risk scenarios, where consequences of privacy are rather vaguely defined without suggesting how users might be damaged (e.g., collection of usage patterns) are perceived the most likely, yet, in terms of severity, rated similarly significant throughout all domains.

Overall, we conclude that privacy risks are well-researched. Within the field of information security, experts' analyses of cyber risks consistently emphasize the importance of privacy risks. The literature points also to a large body of studies in the context of technology acceptance, although there is not yet conclusive agreement on the influence of privacy risks on acceptance.

- *Cyber security.* In contrast to the misuse of personal data associated with privacy risks, cyber security risks refer to vulnerabilities and threats in hardware, software, and data of SH devices and services (Klobas et al., 2019). Technical studies providing risk analysis in this context are numerous. Across all studies, statements can be assigned to one of the following three themes, namely asset, vulnerability, or threat. The interplay of these three aspects leads to the definition of a given cyber risk. For example, Ali et al. (2019) defines

a cyber risk as the potential loss caused to the SH ecosystem by a threat exploiting certain vulnerabilities. Assets are typically defined at the beginning of the risk analysis, based on a given SH architecture (Ali et al., 2019; Jacobsson et al., 2016; Alexandrov et al., 2019). Such assets include sensors, gateways, servers, application programming interfaces, mobile devices, and the mobile device apps. Within these components of the SH architecture, certain categories, such as software, hardware, information, communication protocols, and human factors, are ubiquitous. Overall, the assets that are qualified as risky are mostly those that are used and whose properties are configured by the end user. Thus, cyber risks primarily arise from software and mobile devices and the related applications and services.

Most reviewed studies proceed by identifying vulnerabilities of SHs based on the assets. In particular, the work by Jacobsson et al. (2016) is most comprehensive. In their study, 4 of 32 vulnerabilities result in high risks, 19 are classified as medium risks, 9 are low risks. The most relevant vulnerabilities are poor password selection, sloppy end user, gullible users and software security in applications. They all belong to the asset categories of human factors and software. Various studies emphasize the importance of human factors (e.g., Van Hoorde et al., 2018; Ali and Awad, 2018; Li et al., 2018) and stress the relevance of software vulnerabilities (e.g., Ali et al., 2019).

A threat can be defined as a potential action that results in a loss (Ali et al., 2019). New capabilities of smart homes enable new types of attacks while permitting traditional attacks with novel consequences (Denning et al., 2013). The literature emphasizes this trend and discusses threats in greater detail compared to assets or vulnerabilities. Most studies derive threats on the basis of previously identified vulnerabilities and the assets thereof. Jacobsson et al. (2016) identifies, in order of rank, circumvention of authentication mechanism, social engineering and unauthorized modification to a system as the top three threats to SHs. All are mainly caused by human-software combinations. The authors also note privacy and manipulation threats to hardware and communication protocols. Van Hoorde et al. (2018) emphasizes the fact that hardware-related manipulation should not be neglected, yet prioritize threats linked to privacy disclosure, inadequate access control and malware mitigation. Threats targeted toward smartphones, due to high risk exposure, are considered by Brauchli and Li (2015) the most relevant. Another prominent approach evaluates specific forms of attacks. Thereby, possible attacks from areas, such as information security, are summarized and then evaluated by assessing the vulnerabilities and assets (see Blythe and Johnson, 2019 for an overview). There is a consensus that attacks with denial of service and eavesdropping are main threats (Nurse et al., 2016; Ali et al., 2019). Finally, some concepts take an in-depth look at the threats for a specific SH technology (e.g., RFID, Zigbee and Wi-Fi technologies in Krishnan et al., 2017; Zigbee technology in Wongvises et al., 2017).

In risk analyses from technology acceptance research, the perceived importance of cyber security risks is minimal. Park et al. (2018) attributes minimal influence of cyber security to the overall risk perception, while Wang et al. (2020) attributes none at all. A possible reason for this could be the lack of understanding and the complexity of the topic, which prevents perception at all (Mani and Chouk, 2017). Therefore, Klobas et al. (2019) analyzes cyber security risks separately from other risks.

We conclude that cyber security is a major research subject in information security risk analyses. Human factors and software components are presented as critical sources of

risks. Comparing these results to the technology acceptance literature illustrates how risk assessment depends on the perspective. Users rate the significance of cyber security risks as less important than information security experts.

- *Performance.* The loss in performance of a SH product or service is linked to an emerging performance risk (Hong et al., 2020). Typically, performance risks stem from considerations about topics of broader technological interest and, thus, have almost general applicability to all technologies (Sovacool and Furszyfer Del Rio, 2020). Risks, such as technical reliability, warranties, or obsolescence, should be noted here. In studies from acceptance research, perceived performance risks are largely considered irrelevant (Hubert et al., 2019; Wang et al., 2020). Yet, the work of Park et al. (2018) highlights the perceived performance risks. They categorize the surveyed sample (1008 respondents) into three groups, depending on the resulting level of total risk perception. For the middle group, perceived performance risks resulted as the most significant. Hong et al. (2020) follows a similar approach, dividing the surveyed sample (553 respondents) into SH technology rejecters and postponers. For both, performance risk is perceived as relevant, even if only mediocre.
- *Dependence.* According to Sovacool and Furszyfer Del Rio (2020), there is a risk that SH technologies become a black box for average households, leading to isolation, vulnerability to fraud or lock-in effects. In the study by Wilson et al. (2017), other aspects, like mental aspects of a resulting dependence, are identified (e.g., SH as non-essential luxuries or driver of laziness). In acceptance research, the increase in dependence is studied as the effect of SHs on users' control perception (Sovacool and Furszyfer Del Rio, 2020). Initially, SHs were supposed to increase control. However, usage may also result in a loss of control (Wilson et al., 2017). Such risks potentially have negative effects on the users' peace of mind. Hong et al. (2020) considers that dependence risks become increasingly important and have, for example, stronger influence on the overall risk perception than performance risks.
- *Access to technology.* On a societal level, new risks related to the access to SH technology emerge. From a risk perspective, this is a distinct but cross-cutting risk. The exposure to today's pre-existing risks, such as water or fire, which we will address below, can largely be attributed to socio-economic factors (Banks and Bowman, 2018). Today, it is still unclear whether SHs reinforces the significance of these factors or balance them out socially (Nilson and Bonander, 2020).
- *Social isolation.* Marikyan et al. (2019) and Sovacool and Furszyfer Del Rio (2020) identify two types of social isolation. Besides the social divide in terms of technology access that may emerge, SH technology and services can lead to increasing technology-human interactions, and thereby displace human-human interactions. These considerations are closely related to human detachment concerns, which are a prominent topic in SH acceptance research. Users of SHs may feel disconnected from interpersonal contact and especially in SH studies with elderly users or with a clear health focus, such concerns are dominant (Alaiad and Zhou, 2017).
- *Legal.* A study from the acceptance research area mentions that users perceive a certain risk associated with the lack of corporate accountability of SH vendors (Sovacool and Furszyfer Del Rio, 2020). These considerations embody the user perspective and originate

from unclear regulatory conditions or potentially limited longevity of vendors, as the latter are often start-ups.

- *Time*. Perceived time risk refers to the time wasted when using SH technologies (Wang et al., 2020). However, this risk has been found to be insignificant in other studies (Klobas et al., 2019; Wang et al., 2020).

2.3.2 Pre-existing risks

The literature suggests that SHs have an influence on pre-existing risks, such as fire, water, or burglary. As an example, Blythe and Johnson (2019) state the case where thousands of cameras were exploited by attackers in 2016 and emphasize that the potential form crime can take increases with the use of interconnected devices. Tanczer et al. (2018), studying risk patterns for IoT risk scenarios, rate the SH ecosystem as the most significant affected by this tendency. They conclude that crime exploits an increasing number of cyber-physical dependencies. Thus, it is likely that SHs may lead to an increase in illegal activities for economic, personal or political gain.

- *Theft*. Blythe and Johnson (2019) map specific attacks related to cyber security to pre-existing risks. On the one hand, they emphasize that exploiting insecure SH devices by eavesdropping offers criminals a wider variety of options to perform crimes, such as stalking or burglary. On the other hand, insurance experts (AXA, 2019; Octotelematics, 2019) see significant advantages of SH technologies concerning theft. They refer for example to a study of the Federal Bureau of Investigation (2016), where the probability of a burglary rose by 300% if no preventive measures were in place. Light and camera systems play a crucial role here. One may conclude that crime risk, mainly associated to burglary and theft, is changing, but a consensus is not yet found in the literature. In addition, studies on theft provide some initial indications of connections between SH risks.
- *Waste of resources*. SH is promoted as an important lever for new climate targets. Using the example of intelligent ventilation systems, Psomas et al. (2017) show how SHs can foster a more careful and targeted use of resources. However, other studies show how the increasing data consumption resulting from SH technologies greatly increases global electricity usage (Vidal, 2017) or even daily household labor (Strengers and Nicholls, 2017) and, thus, reinforce unsustainable energy consumption (Tirado Herrero et al., 2018).
- *Financial*. Unexpected additional expenses or loss of income are often the results of household damages (i.e., fire, water, burglary) (Tanczer et al., 2018). The SH context broadens the potential sources of financial consequences. According to a study by Hartford Steam Boiler (HSB) insurance company (Milewski, 2017), 87% of the victims of cyber attacks in the U.S. suffered financial losses. Likewise, derived as a consequence of potentially increased dependence, there is a real risk that SH technologies leads to greater financial dependence (Sovacool and Furszyfer Del Rio, 2020). Thus, emerging risks come with relevant new financial risks and many pre-existing risks ultimately have a financial impact on the household's individual.

In technology acceptance studies, perceived financial risks denote the possibility by which the product or service may not be worth its price (Hong et al., 2020). However, numerous studies find that the influence of perceived financial risks on overall risk perception is not significant (Alaiad and Zhou, 2017; Hong et al., 2020; Kim et al., 2017; Sovacool and

Furszyfer Del Rio, 2020; Wang et al., 2020). The work of Park et al. (2018) is an exception as they point out that, in those that perceive financial risks as low, they have by far the greatest influence on the overall risk perception.

- *Fire.* Average fire-related insurance claims are the most expensive losses for non-SH households (Insurance Information Institute, 2020). Several studies point to SHs' potential in reducing the probability, as well as the severity of a fire incident (Feuerstein and Karmann, 2017). Roost (Goldberg et al., 2019), an insurtech whose business model is built on the use of SH, reports a 15% reduction in claims frequency. BI Intelligence (Meola, 2016) sees even greater potential in reducing the severity of the risk. Banks and Bowman (2018) confirm the potential mitigation of fire risk by SHs. Likewise, in comparison to commercial buildings, the potential of SH technologies for private households becomes especially obvious (Salhi et al., 2019). While the use of SH to prevent and treat fire risk is widely discussed, we found no indication of a change of the underlying risk.
- *Water.* The risk of water damage is assessed in insurance practitioners' studies. Contrary-wise to fire losses, the probability of water damage is high and the severity low (Insurance Information Institute, 2020). ACE Group (2011) points out that 93% of all insurance costs from water damage could be prevented by SH technology. More recently, an empirical study from LexisNexis (Davis, 2020b) confirm the finding by comparing households equipped with and without water sensors. One year after the installation of sensors, SHs saw a 96% decrease in paid water leakage claims and a 72% decrease in claims severity, while the control group recorded a 10% increase in frequency with unchanged severity levels. The risk of flooding has its own major field of research intensively discussing risk treatment measures. SH technology is listed by Azam et al. (2017) for reducing the severity of potential losses.
- *Health.* Many SH use cases seek to promote health and well-being (Alam et al., 2012; Ehrenhard et al., 2014). In contradiction to these benefits, it is unclear whether new health risks arise from SH use (Tanczer et al., 2018; Sovacool and Furszyfer Del Rio, 2020). The literature related to technology acceptance is scarce (Sovacool and Furszyfer Del Rio, 2020). We only found Park et al. (2018) discussing the polarizing issue of electromagnetic radiation. For high risk perceivers, such radiation becomes overwhelmingly salient, while, for moderate and low risk perceivers, radiation leaves a low impact, respectively, negatively affecting the overall risk perception.
- *Other property damage.* Finally, the reviewed literature mentions other pre-existing risks of non-SH households. The risks of property damage, excluding fire and water, that are discussed are for example wind and hail (Feuerstein and Karmann, 2017). Early warning systems based on SH technology demonstrate their positive effect on pre-existing risks. In sum, while SH provides early warning or new risk treatment options, there is no indication of a change in the underlying risk.

In Table 2.1, we provide a summary of the risks identified in the literature. We also indicate the impact of SH on the risks (higher risk "H", lower risk "L", unclear effect "-"). Thereby, three risks result with SH as higher, eight as lower and for four the effect is unclear. Likewise, we indicate how strongly the various risks affect the acceptance of SH by lay users (high influence on acceptance "H", low influence on acceptance "L", unclear effect "-"). Five risks have a

relevant influence on SH acceptance, five have no influence, and, in five others, the effect is unclear. More details on the identified risks are available in Table 2.5 in Appendix 2.7.

Finally, there are interesting attempts to compare the risks of different use cases for a certain technology ecosystem to each other. König et al. (2017) discuss use case risks of ambient assisted living associated with inexperienced users and rank privacy the highest, followed by physical safety, social impact, and poorly secured devices. In contrast, for convenience use cases, i.e., disconnected from health considerations, physical safety is the most relevant, and privacy is ranked explicitly the lowest risk.

We observe that SH technology and related services change the risks landscape associated to a household. Especially, new risks related to technology usage emerge while treatment options for pre-existing risks improve. For the most part, extant research considers risks separately from each other. In particular, emerging cyber risks are well-researched in technical analyses. Further, results from the technology acceptance literature provide new perspectives and lead to the identification of additional risks. We also note that financial aspects are often overlooked. The security and comfort of SHs yields high maintenance and repair costs putting additional financial burden on the owners which may result in the risk of losing financial liquidity. In addition, although SH technology provides additional security, property damage from theft, fire, and water may incur higher costs for repair in SHs compared to other houses. Finally, a comparison of the results indicates that the assessment of risks differs by technical experts and users. Overall, we note that risks are not yet analyzed holistically nor evaluated with consistent metrics. A closer look at the methods and disciplines of risk research in the SH context in the next section confirms this shortcoming.

2.4 Risk evaluation

The results on the risks identified in the previous section illustrate that they are researched from different areas. Accordingly, the choice of methods for their evaluation is broad. The most prominent field of study for risks in SHs is the information security discipline. Three main approaches can be found here: a risk-based, a security-based, and a privacy-based approach. The latter two typically emphasize a technological innovation for risk identification and mitigation (Ali and Awad, 2018; Park et al., 2019; Schiefer, 2015). Conversely, risk-based approaches attempt to address cyber risks comprehensively and focus on risk identification and assessment. Often used methods are, for example, information security risk analysis (Jacobsson et al., 2016), fuzzy set theory (Li et al., 2018), and fault tree analysis (Wongvises et al., 2017). All approaches share the common feature that they assess the risk based on a system's ability to meet three basic goals of system security, namely confidentiality, integrity, and availability (Jacobsson et al., 2014). Cyber risks result from a combination of assets, vulnerabilities and threats and are assessed by means of the probability and severity of the risk. More sophisticated models have evolved from this basis. Jacobsson et al. (2016) use a matrix-like risk map dividing the analysis into architecture components and subcategories derived from information systems. Li et al. (2018) complement the analysis with concepts from grey system theory to cover the relationship between the probability, severity and detection of a system failure. All risk-based methods share a semi-qualitative character. They combine qualitative interview techniques with quantitative assessment methods and validation metrics to varying extents of sophistication. Jacobsson et al. (2016) summarize that mixed methods can accommodate the heterogeneous structure and complex relationships between connected devices and people.

Risk	Description	Impact	Acceptance
<i>Emerging risks</i>			
Privacy	Inappropriate handling, disclosure, or use of data collected by SH system leading to interference to the right to keep personal matters private	H	H
Cyber security	Inadequate use of hardware or software by user, attacker or others, leading to damages, such as denial of service or mal-performance	H	L
Performance	Undesired performance variations resulting from usage of a young technology	–	H
Dependence	Degree of dependence that leads to undesired outcomes, such as loss of choice, lock-in, or anxiety	H	H
Access to technology	Disparities in access to technology due to, e.g., socio-economic factors, unwillingness to share data	–	L
Social isolation	Feeling of loneliness resulting from lacking technology access or increasing substitution of human-human interaction	L	H
Legal	Unclear regulatory conditions or supplier longevity leading to uncertainty regarding accountability	L	L
Time	Disappointing benefits or opportunity costs in relation to time invested	L	L
<i>Pre-existing risks</i>			
Theft	Loss of physical or digital property and non-financial losses as a consequence of unauthorized access, use, and misappropriation	–	–
Waste of resources	Unnecessary or wrong use of money, substances, time, energy, or abilities resulting in waste of resources	L	–
Financial	Unexpected deterioration of the value of SH system or extra expenses or loss of income leading to financial loss	–	L
Fire	Bodily injury, death, property damages, and loss of income resulting from fire in and around the house	L	–
Water	Property damages resulting from water leakage in and around the house	L	–
Health	Impairments of physical and psychological health resulting from use of SH technology	L	H
Other property damage	Non-water or fire related property damage in and around the house	L	–

Note: “Impact” describes the influence of SH on a risk, where “H” stands for higher risk, “L” for lower risk, and “–” for an unclear effect. “Acceptance” describes the risks’ influence on the acceptance of SH, where “H” stands for high influence on acceptance, “L” for low influence on acceptance, and “–” for an unclear effect.

Table 2.1: Overview of the pre-existing and emerging risks identified in the review.

Despite technological maturity, SH technology and service adoption and diffusion rates remain low (Marikyan et al., 2019). Hence, there is a relevant body of literature studying risks in SHs from the perspective of technology acceptance. Since these studies are user-oriented, they describe perceived risks by users as potential downsides to acceptance (Sovacool and Furszyfer Del Rio, 2020). Perceived risks by lay users differ from the objective assessment of an expert. However, while perception is a key driver of risk behavior, it does not change the underlying risk. Various papers examine the influence of perceived risks on technology acceptance using structural equation models (Alaiad and Zhou, 2017; Klobas et al., 2019; Wang et al., 2020). Thereby, the overall risk perception is considered to be composed by individual risks. Some models are derived from resistance theory (Hong et al., 2020; Lee, 2020), while Park et al. (2018) exclusively focus on risk perception without considering the acceptance context. Finally, further studies (Gerber et al., 2019) build on the comparison of risks in SHs with those from other online services and draw conclusions on the relative users' perception of privacy and cyber security risks.

Other risk evaluation methods are based on the international standards for risk management (ISO, International Organization for Standardization, 2018). Analyses building on this framework commonly follow its explicit generic approach. The advantage in that approach is that the standard is ubiquitously applicable to every kind of system, regardless of its type, perspective or size (ISO, International Organization for Standardization, 2018). Thus, frameworks specifically adapted to SH also build on the three phases of risk identification, risk assessment, and risk treatment. When comparing the methodology to other approaches, we observe an emphasis on the risk identification. The advanced SH risk management framework from Nurse et al. (2016) divide the ISO 31000 standard into five phases, with risk identification making up three of the five phases. One of the most recent publications based on ISO 31000 combines elements from the above mentioned information security risk analysis and risk management (James, 2019). In addition to probability and impact of a risk, they introduce an additional factor described as the attractiveness of the targeted system as a compromised system.

Similar to the ISO 31000 framework, several other industry standards are used for risk analysis in SHs. König et al. (2017) provides an overview of relevant industry standards for IoT systems. These approaches pursue risk, cyber-security, or privacy goals. The ISO 27000 standard summarizes best practices on information security, the ISA/IEC 62443 design cyber-security robustness and different publications under NIST SP800 give guidance on cyber vulnerabilities (NIST SP800-53), systems security engineering (800-160), or networks of things (NIST SP800-183). Several security-based or privacy-based frameworks (Nurse et al., 2016; Park et al., 2019; Varghese and Hayajneh, 2018) of the information security discipline refer to these models indicating the incorporation its principles.

Finally, analyses from the insurance discipline also contribute to the methodological portfolio. Understanding and analyzing risks is a key pillar of the insurance business (Sheng et al., 2017). The focus today is on applying actuarial rate making to pre-existing household risks, such as fire, water, and theft. The shift to more sophisticated approaches to analyze behavior-related risks is gaining momentum (Banks and Bowman, 2018). There is agreement on the importance of behavioral data for rate making of household risks. However, no specific methodologies for SHs can be found in the academic literature. For SHs, there are practitioners studies similar to the ones in the area of telematics that refer to models without going into greater depth (Matera

and Salvador, 2018). In addition, claims data analyses can be found that compare loss data from households with and without specific SH products (Davis, 2020b).

In summary, the risk evaluation methods we found can be assigned to five areas: information security, acceptance, risk management frameworks, industry standards and insurance practice. For all but two studies (Li et al., 2018; Nurse et al., 2016), the reviewed works focus on applying risk analysis models to the field of SHs. The two exceptions are conceptual contributions that suggest changes to existing models or combine models to better address specific questions. All disciplines bring their own perspective and, thus, come with certain advantages. As such, the focus on information security has led to various risk evaluation methodologies for cyber security and privacy. Yet, as with the risks themselves, there are still no attempts to evaluate risks on the basis of an integrated risk metric. Such an approach would allow to assess and prioritize risks in SHs relative to each other, to assess risk scenarios with interrelations among several risks, to quantify the impact of SH, or to evaluate investments into risk treatment options.

2.5 Risk treatment

The reviewed literature also provides evidence on how to deal with the identified risks in SHs. This risk treatment is about the selection and implementation of suitable measures to address risks (ISO, International Organization for Standardization, 2018). However, systematic studies are limited to the treatment of cyber risks and are technical. Thereby, we find recommendations that are addressed to SH technology and service providers and those directed to the users.

Among the former are the studies of Klobas et al. (2019) and Sovacool and Furszyfer Del Rio (2020). The focus therein is on initiatives that raise awareness, disseminate knowledge and empower users. The primary goal is to align the perceived level of risk to the objective level. In addition, it is important to consider the user interface of SH systems, devices and services and to enable users to simply participate in the protection of their systems. This is also the direction taken by Jacobsson et al. (2016), referring to the need for a model of security and privacy in the design phase of SHs. Accordingly, SH systems should be designed to provide users with methods to evaluate their own risk exposure, to provide them with security principles, and to point out privacy-sensitive information. The study is the only one that defines highly specific treatment measures for cyber risks aimed at the end-user. Based on the risks presented in Section 2.3, we draw on measures related to human factors and software as they represent a major source of cyber risks. The enforcement of password policies and verification tools represents an effective option for weak passwords, whereas policies and legal contracts are tools to address gullible end-users. Software-related vulnerabilities regarding the authentication mechanism can be mitigated through methods of public key infrastructure-based or multi-factor authentication and the continuous installation of updated software packages when available. However, keeping systems dynamic remains important. Even with security and privacy settings, users should configure their own settings instead of static patterns.

Our final corpus of academic research articles does not expand on treatments beyond cyber risks. However, practitioners' studies explore other risks. Thereby, SH is presented as an actual treatment option to address pre-existing risks in non-SH settings. The statement on SH by (Sevillano, 2018) in the Swiss Re study is exemplary: for water, fire, and theft, the study

Method	Description	References
<i>Information security</i>		
Information security risk analysis	Review of a system’s risk exposure based on its ability to fulfill the three basic goals of system security, i.e., confidentiality, integrity, and availability	Alexandrov et al. (2019); Ali and Awad (2018); Ali et al. (2019); Bondarev and Prokhorov (2017); Jacobsson et al. (2016); Tanczer et al. (2018)
Failure mode and effects analysis	Identification of potential failure modes (causes, effects, and areas) affecting a system’s safety, reliability, and maintainability; integration of the fuzzy set theory to evaluate failure modes and of the grey relational theory to calculate the degree of relation among failure modes	Li et al. (2018)
Fault tree analysis	Boolean logic expressed as tree or diagram, where the top event is the failure of a system, and the other events are components’ failures	Wongvises et al. (2017)
Factor analysis of information risk	Risk measurement based on likelihood and probability, consisting of loss event frequency and magnitude factors that represent threats and damage to assets	Park et al. (2019)
<i>Acceptance</i>		
Technology acceptance models	Structural equation models where predetermined hypotheses of the risks’ influence on acceptance are assessed through, e.g., perceived risk or resistance theories	Hubert et al. (2019); Kim et al. (2017); Lee (2020); Park et al. (2018)
Scenario-based perception differences	Definition of different risk scenarios based on detail level of a resulting consequence (abstract vs. specific) or on the SH use case (health vs. comfort)	Gerber et al. (2019); Hong et al. (2020)
<i>Risk management</i>		
ISO 31000	International risk management standard aiming to develop a common understanding on risk management concepts	James (2019)
Individual enhancements	Frameworks based on ISO 31000 specifically adapted to SH settings	Nurse et al. (2016)
<i>Industry standards</i>		
ISO 27000	Best practice in information security management aiming to manage information risks by information security means	König et al. (2017)
NIST SP800	Frameworks developed to address the security and privacy needs, e.g., systems security engineering (NIST SP800-160) and networks of things (NIST SP800-183)	König et al. (2017)
ISA/IEC-62443	Design framework to improve cyber security robustness and resilience in industrial automation control systems	König et al. (2017)
<i>Insurance</i>		
Actuarial rate making	Determination of the price charged by insurance companies for pre-existing household risks	Sheng et al. (2017); Matera and Salvador (2018)
Claims data analysis	Comparison of insurance claims data from households with and without specific SH products, e.g., water leakage or fire sensors	Davis (2020b)

Table 2.2: Overview of the risk evaluation methods identified in the review.

predicts a 50% reduction of total insurance claims resulting from the use of connected devices (see Section 2.3).

Buying insurance is one option to mutualize risks (ISO, International Organization for Standardization, 2018). We identify literature contributions that discuss new forms of insurance enabled by SHs. The assertion that the individualization of actuarial rate making creates opportunities with respect to insurance access is of particular interest for SH (Banks and Bowman, 2018). Traditionally-rated high-risk households may be more attractive risks for insurance companies thanks to additional shared behavioral data stemming from SHs. The confirmation by practitioners' studies gives further weight to these considerations (Feuerstein and Karmann, 2017). In addition, insurance is a technique to finance risks and serves for compensation of losses from specific risks. For example, emerging cyber security threats often result in a financial loss, and, where available, insurance can be an option that is rapidly implemented. Finally, insurers also act as experts and represent a source of knowledge for risk mitigation.

2.6 Conclusions

With the growing presence of technology and an increasing connectivity in many homes, SH technology and services pose substantial opportunities, but also introduce new risks and change the pre-existing landscape. The dynamics of SHs are fundamentally changing home life and, thus, the risks associated with it. Today, research on SH risks is primarily conducted in the disciplines of information security and technology acceptance. As such, in this literature review we present a comprehensive analysis of the extant research on the identification, evaluation and treatment of SH risks. Our results show that research continues to be technology-focused. With SH, a technology itself, this is obvious. From a risk perspective, however, such a specific focus results in risks being overlooked and hence not being managed holistically. Looking into the findings of SH acceptance studies shows that lay users perceive certain risks differently than experts. Thus, interdisciplinary analysis of the qualified literature is important. Beyond the synopsis on emerging and pre-existing risks, we also summarize the learnings on risk evaluation and risk treatment methods. Thereby, our study contributes to aggregating the findings from research "silos" and provides a more comprehensive risk understanding. Overall, we identify various emerging risks, such as cyber security, privacy, and dependency risks, which households using SH are exposed to. Likewise, we identify existing risks, such as theft, fire, and water, which were already present in non-SH settings.

In complex systems, such as SHs, relationships and dependencies among risks emerge and are greatly relevant. Their occurrence depends on the usage context and the behavior of the user. At present, though, research ignores these relationships. Our review offers a starting point for future research in this field that should take both context and use of SHs into account, as well as distinguish different risk scenarios. In addition, findings from various methods should be aggregated. The current risk assessment research is undertaken with a narrow focus on selected risks, foremost isolated on cyber risks or relating to technology acceptance. Thus, the results form a relative prioritization of the risks under study and their drivers rather than a quantitative assessment of the probability and severity. In our review, we outline the influence that SH technology and services have on risks. However, a systematic assessment of all risks using the same metric is missing. This should also be considered in further research. After all, an assessment is a prerequisite, for SH providers and end-users, to make an informed choice of alternatives or on potential risk treatment measures. Finally, risk exposure considerably depends on the users' behavior. However, risk behavior has yet to become a focal point for SH risk

research. Therefore, future research should take behavioral components into account, not only concerning acceptance, but also with regard to SH usage.

The limitations of this review stem largely from the objective of the research. The intended identification of risks in SH led to a large number of papers that provide partial assessment of the risks identified. Our study takes these risks up where available but is not conclusive. The same applies when taking a risk management perspective. As a literature review, this paper does not ensure a comprehensive systematic identification of risks. Moreover, there are inherent limitations in academic studies on technologies due to the lower speed of research getting published. Our review presents a current picture of the state of research that needs to be updated vis-à-vis the fast-evolving technology concept of SH.

2.7 Appendix

The following tables provide additional information.

Table 2.3: Synopsis of academic research articles identified.

Reference	Region	Type	Method	Key Contents and Main Results	RJ	RE	RT
Alaiad and Zhou (2017)	U.S.	A	Interviews ($N = 15$); survey ($N = 140$)	<ul style="list-style-type: none"> Human detachment concerns as emerging risks for SH healthcare systems adoption Other perceived features are privacy concerns, life-quality expectancy, and cost 	✓		
Alexandrov et al. (2019)	RU	A	Discussion (information security risk analysis)	<ul style="list-style-type: none"> Different types of vulnerabilities lead to similar threats Lack of backups and unprotected communication change integrity of information Based on some protective measures identified, some risks are permissible 	✓		✓
Ali and Awad (2018)	SE	A	Discussion (information security risk analysis)	<ul style="list-style-type: none"> Human factors as largest risk source because of different know-how of SH users Risks related to cyber or information assets score high, e.g., user credentials and mobile personal data user applications stemming from inadequate authentication 	✓		✓
Ali et al. (2019)	SA	A	Discussion (systematic literature review)	<ul style="list-style-type: none"> Risk defined as damage impacting system by a threat advanced from vulnerabilities Various vulnerabilities identified and described, e.g., heterogeneous architecture Various threats identified and described, e.g., DoS or eavesdropping 	✓		✓
Azam et al. (2017)	KR	A	Case study (floods in Mushroom stream region)	<ul style="list-style-type: none"> Frequency and impact of natural disasters native to hydrological events increase In South Korea, floods cause the greatest damage among all natural disasters SH as a potential risk treatment option 	✓		
Balakrishnan et al. (2018)	MY	P	Discussion (systematic literature review)	<ul style="list-style-type: none"> Some factors prevent mass commercialization of SH systems, e.g., interoperability, relevance of extracted data, security and privacy, cost, or societal changes Expectations, user involvement, and capability of the systems act as constraints 	✓		
Blythe and Johnson (2019)	UK	A	Discussion (systematic literature review)	<ul style="list-style-type: none"> At least half of all crime now committed online, IoT represents substantial part Different IoT ecosystems suffer from this trend; home is heavily exposed to it New types of crimes include burglary, stalking, sex crimes, and political subjugation 	✓		
Bondarev and Prokhorov (2017)	RU	P	Discussion (information security risk analysis)	<ul style="list-style-type: none"> Filtering of outward parameters proposed to treat internal SH threats Internal threats are threats to sensor, servers and other hardware components Sensor failures categorized in equipment, software, network, or human factor 	✓		✓
Brauchli and Li (2015)	U.S.	P	Case study (SH digitalSTROM environment)	<ul style="list-style-type: none"> Attack vectors can be grouped into vulnerability categories Categories are server, communication bus, control-device, and third party services Control-device refers to the greatest risk 	✓		
Bugeja et al. (2017)	SE	P	Discussion (information security risk analysis)	<ul style="list-style-type: none"> Threat agents are nations, terrorists, organized crime, hackers, thieves, hackers Threat motivations are curiosity, personal gain, terrorism, and national interests Combination of intruders, motivations, and capabilities lead to a new threat model 	✓		

Table 2.3: *Cont.*

Reference	Region	Type	Method	Key Contents and Main Results	RI	RE	RT
Clark et al. (2015)	UK	A	Discussion (UK fire incidents statistics)	<ul style="list-style-type: none"> - Percentage of dwelling fires relatively to all fires tends to increase in the past decade - Fires are not equally distributed across socio-demographic or geographical domains - Social science should be included in fire risk analysis 	✓	✓	✓
Dahmen et al. (2017)	U.S.	A	Case study (CASAS SH framework)	<ul style="list-style-type: none"> - Improving home security is a practical use case for SH - Monitoring activity-based anomalies supports detection and treatment of threats - Anomalies naturally exist; thus, not all represent security threats 	✓		
Gerber et al. (2019)	DE	A	Survey ($N = 942$, technology acceptance)	<ul style="list-style-type: none"> - Abstract risk scenarios are perceived as likely, but only moderately severe - Specific risk scenarios are perceived as moderately likely, but rather severe - Specific risk scenarios has great influence on users' risk perception 	✓		
Hong et al. (2017)	KR	P	Survey ($N = 533$, technology acceptance)	<ul style="list-style-type: none"> - Perceived risks divided into performance, financial, privacy, and psychological risk - Only minor differences when surveyed sample divided into postponers and rejecters - Exception forms perceived privacy risks and perceived financial risks 	✓		
Hong et al. (2020)	KR	A	Survey ($N = 533$, technology acceptance)	<ul style="list-style-type: none"> - Perceived risks divided into performance, financial, privacy, and psychological risk - Only minor differences when surveyed sample divided into postponers and rejecters - Exception from perceived privacy and financial risks 	✓		
Hubert et al. (2019)	DE	A	Survey ($N = 409$, technology acceptance)	<ul style="list-style-type: none"> - Overall risk perception (ORP) is a valid inhibitor of use intention and acceptance - Perceived usefulness predictors are more significant to acceptance than ORP - Perceived security risk contributes strongest to ORP, followed by performance risk 	✓		
Jacobsson et al. (2014)	SE	P	Interviews ($N = 9$)	<ul style="list-style-type: none"> - Most significant risks result from combination of software and human end-user - Security and privacy mechanisms to be included in design phase of SH - Enforcing privacy in IoT environments is main barrier to realize the vision SH 	✓	✓	
Jacobsson and Davidsson (2015)	SE	P	Interviews ($N = 9$)	<ul style="list-style-type: none"> - Most significant risks result from combination of software and human end-user - Security and privacy mechanisms to be included in design phase of SH - Enforcing privacy in IoT environments is main barrier to realize the vision SH 	✓	✓	
Jacobsson et al. (2016)	SE	A	Interviews ($N = 9$)	<ul style="list-style-type: none"> - Most significant risks result from combination of software and human end-user - Implementation of standard security features significantly reduces software risks - Human factors need careful consideration as they are inherently complex to handle 	✓	✓	✓
James (2019)	U.S.	P	Discussion (authors' expertise)	<ul style="list-style-type: none"> - Recently, there has been a great deal of SH device development - Risk model based on probability, impact, attractiveness as compromised platform - Human factors and security goals considered as main features to determine impact 	✓	✓	

Table 2.3: *Cont.*

Reference	Region	Type	Method	Key Contents and Main Results	RJ	RE	RT
Kim et al. (2017)	KR	A	Survey ($N = 269$, value-based adoption model)	<ul style="list-style-type: none"> – Privacy risk and innovation resistance were found to limit perceived value – Yet, perceived benefits have a stronger influence on perceived value – SH acceptance affected more by positive factors than risks 	✓		✓
Kirkham et al. (2014)	UK	A	Case study (connected washing machine)	<ul style="list-style-type: none"> – Risk-based integrated management of devices improves utilization of home resources – Risk calculated as sum of legal risk, appliance failure risk, and resource security risk – Holistic view on risk includes trust, risk, eco-efficiency, cost, and their relationship 	✓		✓
Klobas et al. (2019)	AU	A	Survey ($N = 415$, technology acceptance)	<ul style="list-style-type: none"> – Perceived security risks have a significant indirect effect on SH adoption decisions – Indirect influence is equally important for acceptance – Guiding users to develop knowledge and skills needed for secure use is key 	✓		✓
Krishnan et al. (2017)	IN	P	Scenario-based analysis (authors' expertise)	<ul style="list-style-type: none"> – RFID security threats are eavesdropping, physical attacks, DoS, and spoofing – For Zigbee, they are replay attack, eavesdropping, data manipulation – For WiFi, they are MITM attacks, eavesdropping, DoS, and packet re-routing 	✓		✓
Lee (2020)	KR	A	Survey ($N = 265$, resistance theory)	<ul style="list-style-type: none"> – Influence of users' privacy concerns on resistance statistically confirmed for SH – Privacy vulnerabilities are categorized into technology, law, provider, and user – User vulnerabilities have the strongest impact on SH users privacy concerns 	✓		✓
Li et al. (2018)	CN	A	Discussion (information security risk analysis)	<ul style="list-style-type: none"> – Effective risk management for smart cities combines different evaluation techniques – Threats in natural, contrived, and physical aspects are most relevant for cyber risks – Policy measures should educate, improve public safety, and provide guidance 			✓
Marikyan et al. (2019)	UK	A	Discussion (systematic literature review)	<ul style="list-style-type: none"> – SHs share three aspects: technology, services, and ability to satisfy users' needs – Perceived risks act as significant barriers to adoption – Technological barriers are the most important factors to be addressed 	✓		✓
Nawir et al. (2016)	MY	P	Discussion (authors' expertise)	<ul style="list-style-type: none"> – Clear outline of various attack types supports development of apt security measures – Resulting taxonomy divides attack types into device property, location, strategy, access level, protocol, information damage, host, and communication stack protocol 	✓		✓
Nilson and Bonander (2020)	SE	A	Survey ($N = 7507$, household panel)	<ul style="list-style-type: none"> – Large risk reductions in fire-related deaths observed in most high-income countries – Reductions are disproportionate for different socio-demographic groups – Household fires remain a considerable societal problem 	✓		✓
Nurse et al. (2016)	UK	P	Discussion (authors' expertise)	<ul style="list-style-type: none"> – Accessibility of security and risk management process promotes risk understanding – Risk frameworks include use case definition, assets & network analysis, threat & attack analysis, risk definition & prioritization, and control definition & alignment 	✓		✓

Table 2.3: *Cont.*

Reference	Region	Type	Method	Key Contents and Main Results	RJ	RE	RT
Park et al. (2018)	KR	A	Survey ($N = 1008$, technology acceptance)	<ul style="list-style-type: none"> Perceived risks include financial, performance, security, privacy, and health risk Electromagnetic radiation (EMR) as one health risk with great influence on ORP Experts emphasize cyber security risks, but users are more likely to perceive EMR 	✓		✓
Park et al. (2019)	KR	A	Scenario-based analysis (FAIR risk analysis)	<ul style="list-style-type: none"> Risk = Threat × Vulnerability × Impact, where Threat × Vulnerability = Likelihood Existing qualitative risk assessments update on risk indicators once determined Risk distribution can change with each scenario, country, and time 	✓		✓
Pechon et al. (2021)	BE	A	Actuarial rate making (policies $N = 842, 896$)	<ul style="list-style-type: none"> Dependence between home and motor insurance claims frequency Multivariate credibility models allow to better identify the riskiest households 	✓		✓
Psomas et al. (2017)	DK	A	Case study (summer window ventilation)	<ul style="list-style-type: none"> Trends towards nearly-zero energy houses increases overheating occurrences indoors Use of automated roof window control system truly decreases overheating risk Comes without any significant compromise of the indoor air quality 	✓		
Salhi et al. (2019)	JP	P	Case study (fire and gas leakage)	<ul style="list-style-type: none"> Smoke and fire detection devices considered as first line of defense to leakage risk Compared to industrial domains, detection systems in residential houses are basic Detection systems work separately and are not embedded in home ecosystem 	✓		
Schiefer (2015)	DE	P	Discussion (authors' expertise)	<ul style="list-style-type: none"> Higher market penetration makes SH devices more attractive for offenders Raw sensors are limited on memory and computing power Lower risk to be target of an attack 	✓		
Sovacool and Furszyfer Del Rio (2020)	UK	A	Interviews ($N = 31$); retail visits	<ul style="list-style-type: none"> Privacy and security risks rank highest, health risk lowest Several other technical issues are seen as barriers to adoption, e.g., reliability Ability to better manage energy services is the most prominent benefit 	✓		
Tanczer et al. (2018)	UK	P	Interviews ($N = 19$, IoT experts)	<ul style="list-style-type: none"> Four emerging risk patterns are extracted for all IoT risk scenarios (incl. home) Physical safety, crime and exploitation, loss of control, and social norms and structures are named 	✓		✓
Varghese and Hayajneh (2018)	U.S.	P	Case study ($N = 7$ popular SH devices)	<ul style="list-style-type: none"> Frameworks for SH product purchase decision are available Almost all products fail to effectively promote security awareness Security awareness is particularly missed on product packaging or product website 	✓		✓
Wang et al. (2020)	AU	A	Survey ($N = 351$, technology acceptance)	<ul style="list-style-type: none"> Individuals ignore potential risks and focus on potential benefits from SH usage Perceived privacy, performance, and time risk significantly influence ORP Perceived security and financial risk have no influence on ORP 	✓		

Table 2.3: *Cont.*

Reference	Region	Type	Method	Key Contents and Main Results	RJ	RE	RT
Wilson et al. (2017)	UK	A	Interviews ($N = 42$); survey ($N = 1025$)	<ul style="list-style-type: none"> - Ceding autonomy and independence are the main perceived risks - Policy-makers can play an important role in mitigating perceived risks - They support design and operating standards, guidelines on data privacy, and more 	✓		
Wongvises et al. (2017)	TH	P	Case study (Zigbee lighting system)	<ul style="list-style-type: none"> - In Fault Trees, top event is systems' failure and basic events components' failures - Events leading to failure are compromising sensors, vulnerable controlling device, infection attack, and DoS attack 	✓	✓	

Table 2.4: Synopsis of practitioners' studies identified.

Reference	Region	Type	Method	Key Contents and Main Results	RJ	RE	RT
ACE Group (2011)	U.S.	R	Discussion (insurance claims, 2007-09)	<ul style="list-style-type: none"> - Water caused annually USD 9.1 billion property losses from 2007 to 2009 - Losses from water claims reflect 23% of all property losses - 93% could be minimized with automatic water leak detection and shut-off system 	✓		✓
Banks and Bowman (2018)	AU	R	Interviews ($N = 75$)	<ul style="list-style-type: none"> - Low-income households live in areas rated high risk with the highest premiums - Improvements in detecting or preventing risks have impact on risk assessment - With access to SH, low-income households may benefit particularly 	✓		✓
Davis (2020a)	U.S.	R	Survey ($N = 2500$, technology acceptance)	<ul style="list-style-type: none"> - SH devices meet needs, such as convenience, energy savings, or desire being modish - Adoption rates of specific devices indicate perception of certain needs - For example, 75% own a smoke detector, 2/3 a thermostat or security installation 	✓		
Davis (2020b)	U.S.	R	Experiment (water sensor claims)	<ul style="list-style-type: none"> - One year with sensor, SH homes saw a 96% decrease in paid water leak claims - Within the same period, control group's claims (without sensor) increased by 10% - Severity decreased by 72% after one year (remained stable in the control group) 	✓		✓
Doulon (2015)	U.S.	I	Case study (wine storage)	<ul style="list-style-type: none"> - Top five claims for wine received by AIG from 2004 to 2014 are water damage (26%), power outage (25%), theft (21%), natural catastrophe (18%), breakage (10%) - SH may reduce severity of loss, especially for power failure or temperature drops 	✓		✓
Fasano et al. (2017)	CH	R	Discussion (authors' expertise)	<ul style="list-style-type: none"> - Time is a key factor when dealing with domestic damages - Cost of damage increases at rate of USD 3000 per fire per minute of response time - Predictive modeling around behavior within the home will become a key domain 	✓		✓

Table 2.4: *Cont.*

Reference	Region	Type	Method	Key Contents and Main Results	RI	RE	RT
Feuerstein and Karmann (2017)	CH	R	Discussion (authors' expertise)	<ul style="list-style-type: none"> - At present, behavior is not taken into account beyond claims data - Studies suggest behavioral changes can significantly reduce risk exposure - Claims data for all insurance-related risks are assessed 	✓	✓	✓
Fitzpatrick (2019)	U.S.	I	Discussion (author's expertise)	<ul style="list-style-type: none"> - Worthwhile SH devices have low acquisition cost compared to premium counterparts - Fire alarms have the most attractive ratio 	✓		
Insurance Information Institute (2020)	U.S.	R	Discussion (insurance claims, 2014–18)	<ul style="list-style-type: none"> - Homeowner losses are ranked by claims severity and frequency - Fire losses are highest in severity, and wind & hail are highest in probability 	✓		
König et al. (2017)	AT	R	Survey ($N = 109$, IoT experts)	<ul style="list-style-type: none"> - Main risk in healthcare settings is that devices are used by inexperienced people - Another risk is that devices may compromise privacy - Devices may also introduce safety hazards 	✓	✓	✓
Marsh Private Client Services (2020)	U.S.	R	Discussion (insurance claims, 2016)	<ul style="list-style-type: none"> - Cooking equipment is leading cause of home fires, igniting 46% of all home fires - In order of priority, candles, electrical causes, heating, and smoking follow 	✓		
Matera and Salvador (2018)	IT	R	Discussion (authors' expertise)	<ul style="list-style-type: none"> - Proposed risk evaluation method builds on objective and quantitative analyses - Measures include maximum possible loss and normal loss expectancy - Novel approaches emphasize importance of risk prevention 	✓	✓	✓
Milewski (2017)	U.S.	R	Survey	<ul style="list-style-type: none"> - 87% of cyber attack victims suffer from financial losses by paying money to attacker - Problem will likely worsen as the number of connected home devices increases - New cyber insurance coverage is one alternative of risk treatment 	✓	✓	✓
Octotelematics (2019)	IT	R	Discussion (authors' expertise)	<ul style="list-style-type: none"> - Traditionally, insurers use proxy data to identify the risk of loss for an asset - IoT gives access to real-time, individual, and observable data on risks - Data is directly actionable for risk pricing and treatment 	✓	✓	✓
Sevillano (2018)	CH	R	Survey	<ul style="list-style-type: none"> - Water, theft, and fire are source of around 50% of insurance claims (2013) - Technology will play a vital role in reducing these risks 	✓	✓	✓
Sheng et al. (2017)	CN	R	Discussion (authors' expertise)	<ul style="list-style-type: none"> - Individual coverage concepts are complex and time consuming - Technology makes these concepts possible within retail and commercial space - Coverage to adapt automatically and real-time to changing life and risk situations 	✓		

Table 2.4: *Cont.*

Reference	Region	Type	Method	Key Contents and Main Results	RJ	RE	RT
Van Hoorde et al. (2018)	BE	B	Discussion (authors' expertise)	<ul style="list-style-type: none"> Threats mainly relate to privacy, inadequate access control and malware mitigation Additional risks to hardware are theft, manipulation and sabotage Overall, the end-user still represents one of the weakest links 			✓

Note: The types of references are coded as follows. "A" = article, "B" = book, "P" = insurance magazine, "P" = proceeding paper, "R" = report. The columns "RJ", "RE", and "RT" stand for = risk identification, risk evaluation, and risk treatment and insurance, respectively.

Table 2.5: Pre-existing and emerging risks identified in the review.

Risk	Source	Events	Consequences	Likelihood	References
<i>Emerging risks</i> Privacy	Bundle of highly sensitive information resulting from SH behavior (e.g., unaware usage or threats linked to privacy disclosure)	Specific cyber attacks directed towards data leakage or unauthorized retention of personal data	Inappropriate handling of personal user data collected from SH	High probability, as privacy experiences fundamental change within SH settings and risk often accepted by users	Gerber et al. (2019); Jacobsson et al. (2016); Klobas et al. (2019); Loi et al. (2017); Park et al. (2019); Sovacool and Furszyfer Del Rio (2020); Tanczer et al. (2018)
Cyber security	Inadequate access control and malware mitigation directed to SHs' user behavior or software (e.g., poor user credentials, identity credential theft, unauthorized modification to systems)	Specific attacks directed at the software-human interface (e.g., eavesdropping, DoS, DDoS)	Damage experienced personally as a user or societal damage building on hijacked personal SH system	High probability, as household-related crime shifts increasingly into the cyber space	Alexandrov et al. (2019); Ali and Awad (2018); Ali et al. (2019); Brauchli and Li (2015); Blythe and Johnson (2019); Denning et al. (2013); Jacobsson et al. (2016); Krishnan et al. (2017); Li et al. (2018); Nurse et al. (2016); Van Hoorde et al. (2018); Wongvises et al. (2017)
Performance	Loss in performance of a SH product or service derived from topics of broader technological interest (e.g., reliability, obsolescence)	n.a.	Uncertainty or experienced loss in performance	n.a.	Hong et al. (2020); Hubert et al. (2019); Park et al. (2018); Wang et al. (2020)

Table 2.5: *Cont.*

Risk	Source	Events	Consequences	Likelihood	References
Dependence	Lack of technical understanding, users' laziness or lack of alternatives to SH	n.a.	Technology dependency or greater laziness with greater levels of usage	n.a.	Alaiad and Zhou (2017); Hong et al. (2020); Sovacool and Furszyfer Del Rio (2020); Wilson et al. (2017)
Access to technology	Technology access disparities related to socio-economic factors or willful non-access	n.a.	Individual isolation from certain SH benefits	n.a.	Nilson and Bonander (2020); Park et al. (2019); Sovacool and Furszyfer Del Rio (2020)
Social isolation	High levels of dependency or non-access to technology	n.a.	Non-access to SH, technology-human interactions displacing human-human interaction or human detachment	n.a.	Alaiad and Zhou (2017); Hong et al. (2020); Park et al. (2019); Sovacool and Furszyfer Del Rio (2020); Wilson et al. (2017)
Legal	Limited longevity of supplier (start-ups) or unclear regulatory conditions	n.a.	Lack of corporate accountability or legal clarity on safeguards in the event of a dispute	n.a.	Sovacool and Furszyfer Del Rio (2020)
Time	n.a.	n.a.	Time wasted when using SH technologies	n.a.	Klobas et al. (2019); Wang et al. (2020)
<i>Pre-existing risks</i>					
Theft	Regional aspects, period, infrastructure, behavior or insecure SH systems	Break-in	Physical or psychological consequences	Low probability, compared to other pre-existing risks, such as water	AXA (2019); Blythe and Johnson (2019); Nurse et al. (2016); Octotelematics (2019); Tanczer et al. (2018); Van Hoorde et al. (2018)
Waste of resources	Unenlightened use of technology and additional devices that are powered and connected to the internet	n.a.	Increase in global electricity usage or increase in daily household labor	n.a.	Hong et al. (2020); Jacobsson et al. (2016); Psomas et al. (2017); Strengers and Nicholls (2017); Tirado Herrero et al. (2018); Vidal (2017)

Table 2.5: *Cont.*

Risk	Source	Events	Consequences	Likelihood	References
Financial	Insecure SH systems or extend by which SHs may not be worth the financial price	n.a.	Financial losses (aggregated from all risks)	High probability, as emerging cyber risks entail new financial consequences and also pre-existing risks often result in financial loss	Alaiad and Zhou (2017); Hong et al. (2020); Kim et al. (2017); Milewski (2017); Park et al. (2019); Sovacool and Furszyfer Del Rio (2020); Wang et al. (2020)
Fire	n.a.	n.a.	Health and financial consequences	Low probability, compared to other pre-existing risks, such as water or theft	Feuerstein and Karmann (2017); Goldberg et al. (2019); Meola (2016); Octotelematics (2019); Salhi et al. (2019)
Water	n.a.	Pipes bursting, water overflow, roof leakage, or frost damage	Water waster (leaks waste more than one trillion gallons of water annually in the U.S.)	High probability, compared to other pre-existing risks, such as fire or theft	ACE Group (2011); Azam et al. (2017); Davis (2020b)
Health	Health-related hazards arising from incorrect use of SH or potentially unknown effects of electromagnetic radiation	n.a.	n.a.	n.a.	Park et al. (2018); Sovacool and Furszyfer Del Rio (2020); Tanczer et al. (2018)
Other property damage	Non-awareness of fragility at certain state	Power outages or long periods of inactivity	Breakage of the item	n.a.	Feuerstein and Karmann (2017)

Note: The dimensions in this table stem from the ISO 31000 standard on risk management (ISO, International Organization for Standardization, 2018). "Source" refers to the element which alone or in combination has the potential to give rise to the risk. "Events" denotes the occurrence or change of a particular set of circumstances. "Consequences" are outcomes of an event affecting the objectives. "Likelihood" is the chance of something happening. "n.a." stands for not available and refers to the fact that no information relating to the dimension can be found in the body of literature.

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Chapter 3

On the Adoption of Smart Home Technology in Switzerland: Results from a Survey Study Focusing on Prevention and Active Healthy Aging Aspects

Smart home (SH) technologies offer advancements in comfort, energy management, health, and safety. There is increasing interest in technology-enabled home services from scholars and professionals, particularly to meet the needs of a growing aging population. Yet, current research focuses on assisted living scenarios developed for elderly individuals with health impairments, and neglects to explore the potential of SHs in prevention. We aim to improve comprehension and guide future research on the value of SH technology for risk prevention with a survey assessing the adoption of SHs by older adults based on novel ad hoc collected data. Our survey is based on the theoretical background derived from the extant body of literature. In addition to established adoption factors and user characteristics, it includes previously unexamined elements such as active and healthy aging parameters, risk and insurance considerations, and social and hedonic dimensions. Descriptive results and regression analyses indicate that a vast majority of individuals acknowledge the preventive benefits of SHs. Additionally, we observe that individuals with higher levels of social activity, technology affinity, and knowledge of SHs tend to report greater interest. Moreover, perceived enjoyment and perceived risk emerge as central elements for SH adoption. Our research indicates that considering lifestyle factors when examining technology adoption and emphasizing the preventive benefits present possibilities for both future studies and practical implementations.

Note: This is a joint work with J. Wagner and A. Zeier Röschmann, published in *Smart Cities* (2024), volume 1, pp. 1-44. The authors would like to thank the participants of the EURAM Conference (2022) and the Annual Conference of the German Association for Insurance Science e.V. (2023) for their feedback on previous versions of this manuscript.

3.1 Introduction

Technology-enabled households ultimately aim to improve the quality of life at home by providing various services that make everyday life at home easier (Chang and Nam, 2021). The umbrella term “smart home” (SH) combines services in the areas of lifestyle and comfort (Chan et al., 2012), energy management (Scott, 2007), health (Alam et al., 2012), and safety (Chang and Nam, 2021). According to the SH literature review by Iten et al. (2021), an SH is defined as “a home equipped with a set of smart technologies that provide a resident with remote, digitized, and automated services that improve his or her quality of life at home.” The definition highlights the three key properties of an SH: the technological aspects of hardware and software, the services enabled by the SH, and the ability to meet specific household needs. SHs pave the way for sustainable change, and technological advances create true interconnectivity between different systems, making the SH much more than a set of individual devices that address isolated needs (Chang and Nam, 2021). Recent market studies indicate that more than 250 SH technologies are commercially available in the UK (Sovacool and Furszyfer Del Rio, 2020). Demand is further expected to increase following the COVID-19 pandemic (Maalsen and Dowling, 2020). As a result, the pandemic crisis and its aftermath have altered people’s daily routines (Ghafurian et al., 2023). The relationship between domestic activities and home technologies has been rethought (Von Humboldt et al., 2020).

Recently, SH research focusing on older individuals has become increasingly important. As people age, they spend more time at home and attach greater importance to it (Alaiad and Zhou, 2014). This is also reflected in the fact that a large proportion sees successful aging as living autonomously at home for as long as possible (Binette and Vasold, 2018). Noteworthy shifts in society, such as the demographic transitions in most industrialized nations and the digital affinity of forthcoming retirees (like the baby boomer generation), marked by a substantial interest in technological support services for daily home life, have provided the stimulus for further research in the field of SHs (Carnemolla, 2018). One area of current research is concerned with the factors that increase the intention to use SHs among older adults (Tural et al., 2021; Nikou, 2019). Older adults are often considered a target group in advanced age or with functional limitations (Turjamaa et al., 2019). Therefore, the focus is mainly on reactive support services (e.g., fall detection) or treating risks that have already manifested. As a consequence, the potential for SHs to enable opportunities for proactive risk prevention has so far been neglected. With risk prevention, we refer to the proactive reduction in the frequency and severity of potential losses experienced at home. In contrast, risk treatment is concerned with managing the consequences of risks.

Against this background, the present research aims to lay the groundwork for investigating the value of SH technology for prevention purposes. The hypothesis guiding this investigation is that older individuals perceive an SH as a valuable instrument to prevent risks at home and, hence, to support active and healthy living at older age. To this end, we review the literature and develop a questionnaire that incorporates features and user characteristics that are potentially relevant from a risk prevention perspective. Although the questionnaire is based on established technology adoption frameworks, we identify several previously unstudied elements of relevance. The concept of active healthy aging (AHA), as advocated by the United Nations, provides a capability-oriented perspective on aging (World Health Organization, 2020). In ad-

dition, our survey considers technology and risk affinity, risk and insurance costs, and social and hedonic dimensions.

The results based on the answers to our survey from 1 515 individuals aged 45 and older in Switzerland provide encouraging insights for studying the preventive value of SHs. The majority recognizes the benefits of prevention in safety-related services. Among all the prevention benefits examined, health benefits have the most pronounced effect on the intention to adopt SHs in the future. Additionally, the results suggest that socially active individuals express greater interest in SHs. Other factors associated with increased interest in SHs among older adults include higher technology and risk affinity, more knowledge about SHs, and the male gender. Finally, there is a clear positive relationship between the enjoyment of using SHs and increased interest in SHs, while perceived risks and costs are identified as barriers to the intention to adopt SHs.

The paper is organized as follows. In Section 3.2, we review the relevant literature to identify potential elements that influence the adoption of SHs and provide examples of preventive services. In Section 3.3, we introduce the survey and describe the measurement items. In Section 3.4, we report descriptive statistics on the collected responses. Furthermore, we present the results of regression analyses assessing the significance of the association of various factors with the intention to adopt SHs. In Section 3.5, we discuss our findings, and in Section 3.6, we conclude.

3.2 Theoretical background

To inform our investigation of the preventive value of SHs for older adults and provide background information, we conducted a literature review. This review included literature on the areas of SH services and prevention, as well as the adoption of SH technology by older adults. The purpose of the literature review is to identify specific preventive elements to complement the development of our survey in Section 3.3.

3.2.1 SH service and prevention areas

Based on the literature, we have identified four main service areas of SH technology: comfort, energy, health, and safety (Shank et al., 2021; Wang et al., 2020; Wilson et al., 2017). Each of these areas offers unique benefits to users (Marikyan et al., 2019a). The *comfort* area covers support services to increase the comfort and lifestyle of residents (Chang and Nam, 2021). The focus is on improving the ability to control various domestic appliances or simplify daily household activities (Li et al., 2021). The *energy* area combines a wide range of services aimed at reducing energy consumption in the house or optimizing energy consumption without human intervention (Große-Kreul, 2022). In addition to considerations related to easier monitoring and control, preventive benefits are also recognized. These benefits are increasingly evident as SHs are discussed in public as an important lever for making private households more sustainable (Schill et al., 2019).

The *health* area relates to services that provide individual health information (e.g., fall detection), or environmental information with relevant health impact (e.g., air quality). From a prevention perspective, it particularly focuses on improving self-management and alerting family

members and professionals in case of emergencies (Große-Kreul, 2022). Currently, most research takes a functional limitations-centered perspective when studying SH health dynamics for older people and refers to seniors of advanced age or disabled persons (Arthanat et al., 2019; Li et al., 2021; Tural et al., 2021). Areas such as ambient assisted living or telemedicine aim to provide technological assistance at home in cases of impairment (Carnemolla, 2018). For instance, these technologies support people with disabilities in achieving a more independent life, enable a self-reliant life in old age, or facilitate the digital transmission of medical information, services, and education (Berkowsky et al., 2017). Turjamaa et al. (2019) argue that researchers should consider SH health services holistically, enabling older adults to perform activities of daily living and lead healthier and more fulfilling lives by enhancing physical safety and social interactions. The AHA concept emphasizes the link between activity and health, encompassing continued participation in social, economic, cultural, spiritual, and civic affairs (World Health Organization, 2002). In 2020, the framework was integrated into a comprehensive 10-year action plan launched by the United Nations, officially known as the UN Decade of Healthy Aging (World Health Organization, 2020). Several studies have highlighted the significance of home life in promoting AHA (Bosch-Farré et al., 2018; Tural et al., 2021), and, at the same time, AHA can be a good predictor of technology adoption (Tacken et al., 2005).

The *safety* area consists of services that allow home occupants to secure their homes and avoid accidents (Chang and Nam, 2021). This area is inherently preventive and commonly associated with preventative benefits (Tural et al., 2021). It encompasses common devices such as door locks, water leak detectors, and motion sensors (Arthanat et al., 2019). In fact, safety products or features are among the most popular SH products in all age groups (Arthanat et al., 2019; Arar et al., 2021). The popularity appears to follow a chronological order, with the most recent innovations being the least preferred (Arthanat et al., 2019). The familiarity of safety-related products can also be attributed to their direct impact on reducing financial losses. Incidents such as water bursts or storms pose well-documented risks, not only in terms of potential losses but also in the attention that they receive from other stakeholders, including insurance companies and homeowner associations (Flückiger and Carbone, 2021).

3.2.2 Factors influencing SH adoption

Among the most important factors promoting SH adoption, the literature points to usefulness and usability (Ayodimeji et al., 2021; Hubert et al., 2019; Shin et al., 2018; Park et al., 2018). These factors have also been confirmed by studies in older adults (Nikou, 2019; Tural et al., 2021). Pal et al. (2018) demonstrate that usability is foremost among older adults, primarily due to the significant effort required to learn any new technology. Another commonly cited factor is the availability of support and resources when using SHs (Sequeiros et al., 2021). Its significance for the acceptance of SHs has been highlighted in some studies (Alaiad and Zhou, 2014; Kim et al., 2017), while other articles suggest that it has no impact (Hoque and Sorwar, 2017; Pal et al., 2018) or even question its reliability (Baudier et al., 2020). Moreover, social influences that relate to the extent to which important others believe one should use an SH receive widespread attention (Alaiad and Zhou, 2014). Yet, we find some studies that question these properties based on age and family composition (Cimperman et al., 2016; Große-Kreul, 2022). Another driver for SH interest is the perceived fun derived from using SHs (Park et al., 2018). The literature review by Marikyan et al. (2019a) reveals that only a few studies investigate this hedonic motivation provided by SHs. However, most of these studies attribute significant influence on

adoption intention (Große-Kreul, 2022; Kim et al., 2017; Park et al., 2017). Eventually, less research attention has been given to factors such as the perceived price value of investing in technology (Tural et al., 2021), habit (Baudier et al., 2020), trust (Shuhaiber and Mashal, 2019), and expert advice (Cimperman et al., 2016), as well as technology anxiety (Arar et al., 2021). Furthermore, Iten et al. (2021) conducted a literature review that provides insights into various barriers and risks that limit SH adoption. It sheds light on the evolving risk landscape associated with SHs, highlighting impediments such as cyber security and privacy and the evolving challenges associated with technology dependency (Loi et al., 2017; Sovacool and Furszyfer Del Rio, 2020). These risks often manifest through financial costs and therefore must be carefully considered. Pal et al. (2018) note that, for older adults, the cost of technology may serve as a notable barrier.

Methodologically, studies on SH adoption mostly rely on technology adoption frameworks that trace back to the seminal work of Davis (1989). As summarized in Table 3.1, most of the factors mentioned above can be related to the traditional technology acceptance model (TAM) and the unified theory of acceptance and use of technology (UTAUT). The TAM incorporates two key constructs related to usefulness and usability (Hubert et al., 2019), while the UTAUT posits that, apart from technology-specific features, personal beliefs can specifically explain an individual’s intentions to use new technologies (Große-Kreul, 2022). The application of the UTAUT framework in the context of an SH was first carried out by Alaiad and Zhou (2014), who concluded that it may be the most integrative research theory to follow given its validity in various technology settings. Furthermore, recent studies on SH adoption (Baudier et al., 2020; Große-Kreul, 2022; Ayodimeji et al., 2021) underscore the comprehensive nature and substantial empirical support of the framework. For instance, Sequeiros et al. (2021) demonstrate that UTAUT-specific beliefs related to hedonic and social factors may exert significant influence on SH adoption.

3.2.3 User characteristics

Research characterizing (potential) users is available, although the results are sometimes contradictory. Regarding age, the adoption intention of younger adults is often found to be higher than that of older ones (see, e.g., Wang et al. (2020)). However, Shin et al. (2018) and Klobas et al. (2019) have observed higher adoption rates among older adults, noting their increased willingness to share personal data in SH health settings. The evidence regarding the effect of gender is also divergent. Sovacool et al. (2021) suggest that SH dynamics are generally strongly influenced by gender, as benefits related to entertainment value or household work differ significantly by gender. These dynamics are particularly pronounced among older individuals and tend to positively influence adoption rates among men (Tural et al., 2021). The evidence on the influence of income and education shows that higher levels come with higher SH interest (Klobas et al., 2019). However, Chang and Nam (2021) suggest that this effect may be related to the costs of technology. One study, including marital status (Arthanat et al., 2019), found that being in a relationship is related to higher SH adoption intention. Additionally, various aspects of technological experience and affinity have been studied. For example, prior experience with SHs has been shown to facilitate adoption (Shank et al., 2021). Awareness and knowledge of SH technologies (Wilson et al., 2017) and ownership of other technologies (De Boer et al., 2019) also lead to higher adoption rates. Smartphone ownership and expertise have been linked to

Factor	Framework	References
Usefulness	UTAUT	Alaiad and Zhou (2014); Ayodimeji et al. (2021); Baudier et al. (2020); Cimperman et al. (2016); Große-Kreul (2022); Hoque and Sorwar (2017); Pal et al. (2018); Sequeiros et al. (2021)
	TAM	De Boer et al. (2019); Hubert et al. (2019); Kuebel and Zarnekow (2015); Marikyan et al. (2019b); Nikou (2019); Park et al. (2017); Shin et al. (2018); Shuhaiber and Mashal (2019); Tural et al. (2021)
	Other	Kim et al. (2017); Luor et al. (2015); Schill et al. (2019); Wang et al. (2020)
Usability	UTAUT	Alaiad and Zhou (2014); Ayodimeji et al. (2021); Baudier et al. (2020); Cimperman et al. (2016); Große-Kreul (2022); Hoque and Sorwar (2017); Pal et al. (2018); Sequeiros et al. (2021)
	TAM	De Boer et al. (2019); Hubert et al. (2019); Kuebel and Zarnekow (2015); Marikyan et al. (2019b); Nikou (2019); Park et al. (2017); Shin et al. (2018); Shuhaiber and Mashal (2019); Tural et al. (2021)
	Other	Wang et al. (2020)
Support & resources	UTAUT	Alaiad and Zhou (2014); Ayodimeji et al. (2021); Baudier et al. (2020); Cimperman et al. (2016); Hoque and Sorwar (2017); Pal et al. (2018); Sequeiros et al. (2021)
	Other	Kim et al. (2017)
Social influences	UTAUT	Alaiad and Zhou (2014); Ayodimeji et al. (2021); Baudier et al. (2020); Cimperman et al. (2016); Große-Kreul (2022); Hoque and Sorwar (2017); Pal et al. (2018); Sequeiros et al. (2021)
Hedonic motivation	UTAUT	Baudier et al. (2020); Große-Kreul (2022); Sequeiros et al. (2021)
	TAM	Marikyan et al. (2019b); Park et al. (2017); Shuhaiber and Mashal (2019)
	Other	Kim et al. (2017)
Risks & barriers	UTAUT	Alaiad and Zhou (2014); Arar et al. (2021); Cimperman et al. (2016); Pal et al. (2018)
	TAM	Hubert et al. (2019); Marikyan et al. (2019b); Nikou (2019); Shin et al. (2018); Shuhaiber and Mashal (2019)
	Other	Furszyfer Del Rio et al. (2021); Hong et al. (2020); Kim et al. (2017); Klobas et al. (2019); Luor et al. (2015); Wang et al. (2020)
Price value	UTAUT	Baudier et al. (2020); Sequeiros et al. (2021)
	TAM	Tural et al. (2021)
Habit	UTAUT	Baudier et al. (2020); Sequeiros et al. (2021)
Trust	Other	Furszyfer Del Rio et al. (2021); Luor et al. (2015)
Expert advice	UTAUT	Cimperman et al. (2016); Pal et al. (2018)
Technology anxiety	UTAUT	Arar et al. (2021); Cimperman et al. (2016); Hoque and Sorwar (2017); Pal et al. (2018)

Note: UTAUT stands for the Unified Theory of Acceptance and Use of Technology, TAM refers to the Technology Acceptance Model.

Table 3.1: Factors influencing SH adoption and their relation to technology adoption frameworks.

higher levels of SH adoption (Tural et al., 2021). The positive influence of technology affinity has been validated by Hubert et al. (2019), among others. Also, home ownership (Arthanat et al., 2019) and household size (Tural et al., 2021) have been found to relate to SH adoption. In Table 3.2, we list the variables characterizing users found in the literature.

Characteristics	Population	References
Age	General	Hoque and Sorwar (2017); Klobas et al. (2019); Li et al. (2021); Sequeiros et al. (2021); Shank et al. (2021); Shin et al. (2018); Tural et al. (2021); Wang et al. (2020)
Gender	Older Adults	Arthanat et al. (2019); Ayodimeji et al. (2021); Chang and Nam (2021); Cimperman et al. (2016); Tural et al. (2021)
	General	Nikou (2019); Shin et al. (2018); Sovacool et al. (2021); Yang et al. (2017)
Education	Older Adults	Chang and Nam (2021); Tural et al. (2021)
	General	Klobas et al. (2019); Shin et al. (2018)
Income	Older Adults	Chang and Nam (2021); Shank et al. (2021); Tural et al. (2021)
	General	Shin et al. (2018)
Martial status	Older Adults	Arthanat et al. (2019)
SH experience	Older Adults	Chang and Nam (2021)
	General	Nikou (2019); Shank et al. (2021); Yang et al. (2017)
SH knowledge	Older Adults	Ayodimeji et al. (2021); Balta-Ozkan et al. (2013); Marikyan et al. (2019b); Wilson et al. (2017)
Technology ownership	Older Adults	Arthanat et al. (2019); Tural et al. (2021)
	General	De Boer et al. (2019)
Technology affinity	Older Adults	Arar et al. (2021)
	General	Hubert et al. (2019); Wilson et al. (2017)
Home ownership	Older Adults	Arthanat et al. (2019); Tural et al. (2021)
Household size	Older Adults	Peek et al. (2015); Tural et al. (2021)
AHA	Older Adults	Carnemolla (2018); Tacken et al. (2005)

Table 3.2: Variables characterizing (potential) SH users.

3.3 Methodology and data

This study investigates the intention to adopt SHs and focuses on the preventive benefits of SH technology for active and healthy aging. The aim is to enhance comprehension and guide future research on the topic by creating new survey data. The subsequent section outlines the structure and design of the survey and the data collection process and explains the variables measured in the survey.

3.3.1 Survey design and data collection

We begin by showing how the concepts of prevention, as well as the elements of SH adoption and user characteristics outlined in Section 3.2, are integrated. We provide a detailed description of

our study design and data collection process. We outline the key components of the questionnaire, the procedures used to obtain a representative survey sample, and how we derived the SH scenario.

Structure The survey is structured along the main topics that we illustrate in Figure 3.1. In the introductory section, we assess the eligibility of participants using filter criteria and quotas related to level of SH knowledge, age, gender, and region of residence. To provide context and guidance, we present an SH scenario that illustrates two use cases. The core of the survey contains 122 questions organized into four categories (personal characteristics, evaluation of prevention benefits, dimensions of SH adoption, risks and costs) and 15 topics labeled from A to O. First, to characterize an interested user, we collect socio-demographic variables, AHA-related parameters, technology and risk affinity, and information about individual insurance coverage. Second, we collect participants’ evaluations of the benefits of prevention in terms of comfort, safety, health, and fitness. Third, we capture key elements influencing SH adoption, including performance and effort expectancies, facilitating conditions, social influences, and hedonic motivation. Finally, we ask about risks and costs. We describe the survey questions in more detail in Section 3.3.2.

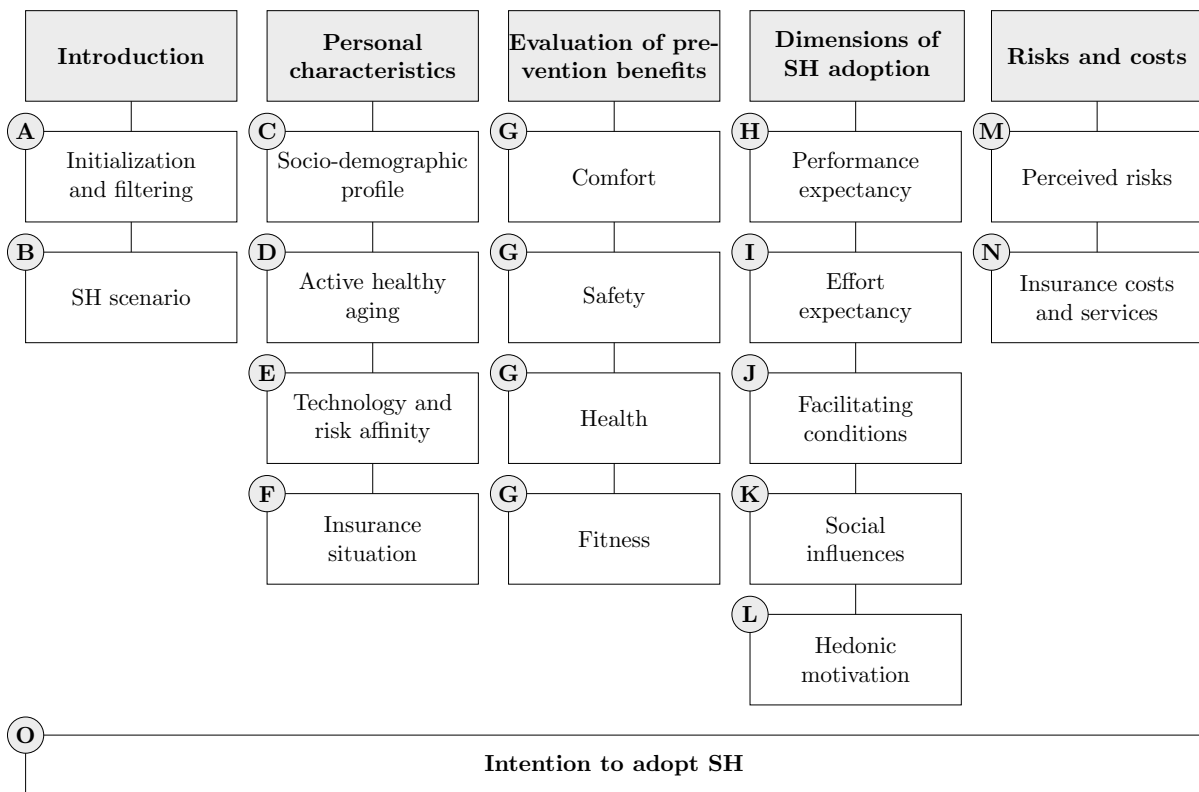


Figure 3.1: Synopsis of the main topics and parts of the questionnaire.

SH scenario As our objective is to survey the behavioral intentions of potential users rather than their actual use or choice of a specific product component, we employ adapted scenarios. The scenario technique, as described by Hubert et al. (2019) for surveys on SHs, offers two approaches: a detailed or abstract scenario description. The literature review by Marikyan et al. (2019a) reveals that most scholars focus on a detailed description of a standalone SH de-

vice rather than a fully interconnected SH system. This approach emphasizes specific services rather than broader lifestyle concepts (Turjamaa et al., 2019), resulting in better respondent understanding. Conversely, an abstract description that encompasses multiple interconnected SH products enables the analysis of preferences for different services (Chang and Nam, 2021). However, this approach has limitations in terms of scenario comprehensibility and potential biases. The literature suggests minimizing these issues by using filter questions to assess respondents' level of SH knowledge (Pal et al., 2018).

We chose an abstract scenario with multiple examples to capture the preferences for different prevention benefits. To ensure the scenario's effectiveness and appropriateness, we implemented a quota for SH knowledge levels allowing fewer than 10% of respondents with no SH knowledge, maintained a summary of the scenario pinned to the top of the screen throughout the survey, and incorporated Swiss-specific household characteristics into the scenario description based on a site visit to a major provider of SH solutions (Bonacasa, 2021). The scenario description can be found as part of the questionnaire in Appendix 3.7, part B.

Operationalization The survey was conducted online in March 2022 using the Unipark software and administrated by a professional polling agency responsible for participant recruitment. Participants were provided financial incentives for successful completion and only given the title of the survey when first contacted. The survey was conducted in both the German and French language. An English translation of the questionnaire is provided in Appendix 3.7. Prior to its distribution, we conducted a pilot test with individuals who met the eligibility criteria to ensure comprehensibility, usability, and technical functionality (see the test protocol in Appendix 3.7). The overall design process follows the CHERRIES guideline (Eysenbach, 2004) for online surveys, and the reporting checklist can be found in Appendix 3.7.

Sample A total number of 2 553 participants were recruited, with 2 490 agreeing to participate. We applied filters based on age (≥ 45 years) aligning with the research focus on AHA, quotas (67:33 ratio for German- and French-speaking regions in Switzerland; 50:50 for female and male; 30:30:30:10 for age groups 45–54, 55–64, 65–74, and over 75 years; 10:90 for participants without and with SH knowledge, respectively), and conducted quality checks throughout the survey using control questions. Note that the distribution of age groups is not fully representative of Switzerland. In particular, the relatively under-represented 10% of those aged 75 and over is due to practical constraints during the recruitment process. The exact distribution should ideally be 30:30:20:20. These considerations should be taken into account when interpreting the results. The final sample consists of 1 515 valid responses and the data presented in this study are being prepared for open access; see Iten et al. (2023).

3.3.2 Questions and measurement items

Using the structure of the questionnaire illustrated in Figure 3.1, we describe the questions and variables measured in our survey. An overview of the variables is provided in Tables 3.3–3.6.

Intention to adopt SH To measure the main variable of interest, the intention to adopt SHs, we use three items. Questions O1 to O3 ask respondents to indicate their level of agreement (on a five-level Likert scale (Likert, 1932) from “strongly disagree” to “strongly agree”) with the statements “*I intend to use smart home in the future.*”, “*I predict I would use smart home*

in the future.”, and *“If the opportunity presents itself in the near future, I will use smart home.”*. The questions were presented in connection with the SH scenario visualization pinned to the top of the screen and are drawn from previous SH adoption studies (see, e.g., Große-Kreul (2022), Baudier et al. (2020)).

Introduction This part includes variables related to filtering, quotas, and the SH scenario examples.

Initialization and filtering. Question A1 collects the self-assessed level of knowledge of SH technologies on a five-level Likert scale ranging from “no knowledge” to “very good knowledge”. In question A2, we ask for the age of the respondent. We code the numeric responses ranging from 45 to 90 years into four categories (45–54, 55–64, 65–74, 75+ years). Question A3 assesses gender with four answer options: female, male, diverse, and prefer not to respond. The respondent’s choice of survey language, German or French, is also recorded. According to the polling company, the selected language is strongly related to the respondent’s origin from the respective linguistic region of Switzerland (i.e., German- or French-speaking region).

SH scenario. Questions B1 and B2 assess preferences for two SH scenario examples using an ordinal scale ranking from “dislike” to “like”. The convenience application (B1) covers generic control and command functions using SHs. The health application (B2) describes functions aimed at controlling and simplifying the delivery of health information.

Personal characteristics To obtain the respondents’ characteristics, we use variables relating to socio-demographic, AHA, technology and risk affinity, and insurance situation. While several variables are self-explanatory, others require a more detailed explanation.

Socio-demographic variables. In question C1, we record the education of the respondent along three categories (mandatory school, high school or professional education, and higher education). Wealth is measured through two questions assessing income sufficiency for recurring expenses (C2) and the ability to cover an unexpected expense (C3). Question C4 inquires about the professional situation, while the home ownership is coded from question C5 into rent and ownership. Additionally, marriage status and different household compositions (single, with kids, etc.) are recorded from questions C6.1 to C6.6.

Active healthy aging variables. While there are different frameworks used to measure AHA (Calasanti and Repetti, 2017), we build on the dimensions of physical, mental, and social well-being from Bosch-Farré et al. (2018) and derive our variables from Börsch-Supan (2022). For the physical dimension, we assess the level of physical activity through questions D1.1 and D1.2, which inquire about the frequency of mildly and very strenuous activities (hardly ever, once to twice per month, once per week, more than once a week). Question D2 focuses on the degree of frailty in certain daily activities. Mental well-being is recorded from questions on satisfaction with life (D3), depressive symptoms (D4), and feelings of loneliness (D5). Social well-being (questions D6.1–D6.7) is evaluated based on the frequency of participation in six different activities (cultural activities, group sports, educational courses, voluntary work, club activities, and going out with friends), and whether one regularly cares for grandchildren as a grandparent.

Label	Description	Categories	Question
<i>Knowledge and preference variables</i>			
Knowledge level	Level of experience in SH	Five levels from <i>no knowledge</i> to <i>very good knowledge</i>	A1
Convenience application	Preference for sensors in the housing	Five levels from <i>dislike</i> to <i>like</i>	B1
Health application	Preference for mobile health device	"	B2
<i>Socio-demographic variables</i>			
Survey language	Chosen language of the questionnaire	German, French	n.a.
Age	Age class in years	45–54, 55–64, 65–74, 75+ (from numeric answers)	A2
Gender	Gender of the respondent	Female, male, diverse, prefer not to reply	A3
Education	Highest level of education	Mandatory school, high school, higher education	C1
Income sufficiency	Income sufficiency for recurring expenses	With great difficulty; with some difficulty; fairly easily; easily	C2
Expense capacity	Ability to cover an unexpected expense	No, yes	C3
Professional situation	Current employment situation	Retired, employed, unemployed, homemaker, unable to work	C4
Home ownership	Main residence ownership	Rent, ownership	C5
Marriage/partnership	Living with spouse/partner in a household	No, yes	C6.1
Single household	Living alone (without anyone else)	"	C6.2
Household with kid(s)	Living with kids in one household	"	C6.4
Other households	Living in other household constellation	"	C6.3,5,6
<i>Active healthy aging variables</i>			
Mildly strenuous activities	Physically mildly strenuous activities	Hardly ever, 1-2x month, 1x week, >1x week	D1.1
Really strenuous activities	Physically really strenuous activities	"	D1.2
Frailty	Frailty in certain everyday activities	No, yes	D2
Satisfaction with life	Satisfaction with current life situation	Five levels from <i>completely dissatisfied</i> to <i>completely satisfied</i>	D3
Depressive symptoms	Feeling sad or depressed	No, yes	D4
Loneliness	Feeling lack of companionship	Almost never or never, 1-2x month, 1x week, >1x week	D5
Cultural activity level	Participation in cultural activities	Hardly ever, few times a year, 1-2x month, 1x week, >1x week	D6.1
Group sports involvement	Participation in group sports	"	D6.2
Educational courses	Participation in educational courses	"	D6.3
Voluntary work	Participation in voluntary work	"	D6.4
Club activity level	Participation in club activities	"	D6.5
Outgoing level	Going out with friends	"	D6.6
Active grandparent	Looking after grandchildren	"	D6.7
<i>Technology and risk affinity variables</i>			
Technology experimenter	Pleasure in trying new technologies	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	E1
Technology pioneer	First to try new technologies	"	E2
Technology expert	Skills using smartphone or tablet	Five levels from <i>poor</i> to <i>excellent</i>	E3
Mistake avoider	Potential errors discourage from usage	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	E4
Familiarity preferer	Familiar things are preferred over new ones	"	E5
Risk-taking level	Self-assessed preferences for risky behaviour	Five levels from <i>not at all</i> to <i>very willing to take risks</i>	E6
<i>Insurance situation variables</i>			
Suppl. health insurance	Supplementary health insurance	No, yes	F1.1
Motor vehicle insurance	Motor vehicle insurance	"	F1.2
Travel insurance	Travel insurance	"	F1.3
Liability insurance	Liability insurance	"	F1.4
Life insurance	Life insurance	"	F1.5
Household insurance	Household insurance	"	F1.6
Legal expenses insurance	Legal expenses insurance	"	F1.7
Other insurance	Other less frequent insurance contracts	"	F1.8
Insurance app in use	App from any insurance company in use	"	F2

Table 3.3: Summary of the variables used in the survey (part 1 of 4).

Technology and risk affinity variables. These variables are derived from established concepts in research on technology adoption and on decisions about insurance take-up. We measure technology affinity via the level of agreement (five levels from “strongly disagree” to “strongly agree”) on statements related to the pleasure in trying new technologies (E1) and readiness to try out new technologies (E2). Respondents rate their own technology expertise in smartphone skills on a five-level scale in question E3. Risk aversion is assessed through the level of agreement about mistake avoidance (E4) and preference for familiarity (E5). Finally, in question E6, we ask respondents to rate their willingness to take risks on a five-level scale from “not at all willing” to “very willing”.

Insurance situation variables. When users put more effort into prevention, the value of existing risk protection and risk financing schemes is reassessed. The insurance sector is increasingly recognizing the importance of data-driven prevention and loss reduction measures (Flückiger and Carbone, 2021). Question F1 captures the respondent’s existing insurance portfolio across eight areas. Additionally, we inquire about the use of an app from the insurer in question F2.

Evaluation of prevention benefits Capturing preferences for prevention considerations in SHs is a crucial aspect of this survey. For the investigated population in the context of AHA, we have identified comfort, safety, health, and fitness as relevant potential benefits. In part G of the questionnaire, we measure the level of agreement (five levels from “strongly disagree” to “strongly agree”) with various statements related to the potential usefulness of SHs. Building on the work of Nikou (2019) for comfort benefits, we query on convenience aspects related to burden relief, home information, and value enhancement in G1.1 to G1.3. The items regarding sense of safety (G2.1), security booster (G2.2), and risk protection (G2.3) in the safety benefits are derived from Luor et al. (2015). To evaluate health benefits, we adapt statements from Cimperman et al. (2016) to include specific forms of health prevention, such as health maintenance, health monitoring, health encouragement, accident prevention, and family well-check (G3.1-G3.5). For the fitness benefits, we introduce new items focusing on exercise at home. The statements cover automated fitness (G4.1), exercise feedback (G4.2), movement motivation (G4.3), and socializing opportunity (G4.4). An overview of the variables related to the evaluation of all prevention benefits is found in Table 3.4.

Label	Description	Question
<i>Evaluation of prevention benefits</i>		
Burden relief	Reduce burden of household activities	G1.1
Home information	Provide information and control options	G1.2
Value enhancement	Maintain or increase property value	G1.3
Sense of safety	Make feel more safely	G2.1
Security booster	Increase home security	G2.2
Risk protection	Protect against risks at home	G2.3
Health maintenance	Take care of oneself and avoid doctor visit	G3.1
Health monitoring	Monitor easily health metrics	G3.2
Health encouragement	Motivate to behave healthier	G3.3
Accident prevention	Help to prevent accidents and health risks	G3.4
Family well-check	Check if family and friends are well	G3.5
Automated fitness	Do automatically something for fitness	G4.1
Exercise feedback	Get immediate feedback on fitness exercises	G4.2
Movement motivation	Motivate to move more	G4.3
Socializing opportunity	Meet new people for training groups	G4.4

Note: All variables are categorical with five levels from *strongly disagree* to *strongly agree*.

Table 3.4: Summary of the variables used in the survey (part 2 of 4).

Dimensions of SH adoption To reliably gather the elements related to SH adoption, we incorporate a minimum of three questions per subject. An overview is provided in Table 3.5. We build on the UTAUT framework as it is the most frequently used in SH adoption studies (see Section 3.2.2). Given the specific context of our analysis, we also introduce new items derived from a literature review and 14 qualitative interviews. Interviews were conducted with randomly selected policyholders from a large Swiss insurer. To ensure validity, we coded the literature and interviews deductively and inductively according to Mayring (2014). The qualitative content analysis was performed using the nVivo software. Each statement in the following sections measures the level of agreement on a five-level Likert scale ranging from “strongly dis-

agree” to “strongly agree”.

Performance expectancy. With performance expectancy, we record the utilitarian value and perceived benefits respondents associate with using SHS (Ayodimeji et al., 2021). The items encompass everyday household activities simplification (H1), home monitoring (H2), activity motivation (H3), money saving (H4), and social connectivity (H5), as well as shared access with others (H6), and allow us to measure performance expectancy following the original UTAUT ideas of Venkatesh et al. (2003) adapted to our SH scenario.

Effort expectancy. Effort expectancy reflects the perceived ease of using SH (Sequeiros et al., 2021). Building on the work of Große-Kreul (2022) and extending the original UTAUT idea to capture the degree of customizability, we cover respondents’ beliefs on easiness to use (I1.1), intuitive understanding (I1.2), easiness to learn (I1.3), quick usability (I1.4), possibility for customization (I2.1), tailoring to the user (I2.2), trustworthiness (I3.1), and warranties (I3.2), as well as autonomous (I4.1) and seamless usage (I4.2).

Facilitating conditions. Facilitating conditions refer to the degree of support and available resources for using SHs, considering both personal capabilities and compatibility with other technologies (Hoque and Sorwar, 2017; Sequeiros et al., 2021). Based on the observations of Ayodimeji et al. (2021) and similar findings in our interviews, we include items that cover both private and professional support dimensions. The proposed statements include assumptions on the availability of usage instructions (J1), of a professional for questions (J2) and when problems arise (J3), of close people (J4) and colleagues or friends for help (J5), and of own knowledge (J6). Finally, we inquire on the importance of how the SH fits into daily life (J7) and in the way the respondent organizes the household (J8).

Social influences. Social influences encompass the extent to which others believe the SH should be used (Ayodimeji et al., 2021). It captures how individuals adjust their opinions, revise their beliefs, or change their behavior as a result of social interactions (Venkatesh et al., 2012). Our interviews identified an additional component related to the belief that SH usage reflects a modern image (Wang et al., 2020). Thus, the statements include the meaning of SHs to important others (K1) and to opinion makers (K2). Furthermore, two statements relate to a more prestigious (K3) and modern image (K4).

Hedonic motivation. SH usage can bring fun, entertainment, or pleasure (Große-Kreul, 2022). According to Marikyan et al. (2019b), different components of hedonic motivation are relevant across different service areas. Owing to our SH scenario including two different applications, we propose a set of ten statements (L1–L10) relating to variety, curiosity, and convenience. The statement includes the characterizations of entertaining, enjoyable, convenient, curiosity-inducing, versatile, fun, pleasant, relieving, trending, and variegating.

Risks and costs In a distinct section, we present SHs in the context of risks and cover aspects related to insurance. The variables utilized to measure those are reported in Table 3.6.

Perceived risks. Here, we capture the perceived risks associated with SH usage. A review conducted by Iten et al. (2021) identified privacy and cost components as the most commonly

Label	Description	Question
<i>Performance expectancy</i>		
Everyday simplification	Simplify everyday household activities	H1
Home monitoring	Monitor effectively state or progress of home	H2
Activity motivation	Motivate to do activities that don't like to do	H3
Money saving	Save money with technology usage	H4
Social connectivity	Stay in touch with family and friends	H5
Shared access	Give access to others when needed	H6
<i>Effort expectancy</i>		
Easy to use	Designed to be easy to use	I1.1
Intuitive	Designed to be intuitively understandable	I1.2
Easy to learn	Designed to be easy to learn	I1.3
Quickly usable	Designed to be quickly usable	I1.4
Customizable	Designed to be individually customizable	I2.1
Tailored	Designed to be tailored to one properly	I2.2
Trustworthy	Designed to be trustworthy	I3.1
Warranted	Designed to be backed by credible warranties	I3.2
Autonomous	Designed to be used without consulting others	I4.1
Seamless	Designed to be used independently without problems	I4.2
<i>Facilitating conditions</i>		
Availability of usage instructions	Instructions available on proper usage	J1
Availability of a professional for questions	Professionals available if any questions	J2
Availability of a professional when problems	Professionals available if any system problems	J3
Availability of close people	Close people available if any difficulties	J4
Availability of colleagues/friends	Colleagues or friends are happy to support	J5
Availability of own knowledge	Sufficient knowledge required for usage	J6
Fit to daily life	Fit well into daily routine	J7
Fit to household	Fit well to household organization	J8
<i>Social influences</i>		
Meaning to important others	Important people encourage technology usage	K1
Meaning to opinion makers	Valued opinions encourage technology usage	K2
Prestigious image	Users have a more prestigious image	K3
Modern image	Users are perceived as modern	K4
<i>Hedonic motivation</i>		
Entertaining	Using SH is entertaining	L1
Enjoyable	Using SH is enjoyable	L2
Convenient	Using SH is convenient	L3
Curiosity-inducing	Using SH arouses curiosity	L4
Versatile	Using SH is versatile	L5
Fun	Using SH is fun	L6
Pleasant	Using SH is pleasant	L7
Relieving	Using SH brings relief	L8
Trending	Using SH helps to be at the pulse of time	L9
Variegating	Using SH leads to more variety in everyday life	L10

Note: All variables are categorical with five levels from *strongly disagree* to *strongly agree*.

Table 3.5: Summary of the variables used in the survey (part 3 of 4).

mentioned risks, along with dependency and loss of control. We consider the increased dependence (becoming dependent on technology, losing control) in statements M1.1 and M1.2. In statement M2.1 and M2.2, we enquire on the costs exceeding benefits, and the SH being expensive to purchase and maintain, respectively. Two statements on misuse (M3.1) and unforeseeable usage of data (M3.2) relate to privacy. Other perceived risks relate to the SH being overwhelming (M4.1) or cumbersome (M4.2), making people leave their house less (M5), and being a non-essential luxury (M6). Finally, we ask the opinion on whether the SH could be a source of problems (M7.1), be insecure (M7.2), replace contact with others (M8.1), and result in a lack of human interaction (M8.2).

Insurance costs and services. Several practitioner studies (Davis, 2020a,b; Sevillano, 2018) discuss the value proposition of the SH from the perspective of insurance companies. In this section of the survey, we propose to the respondents that they could obtain SH services from an insurance company. The insurer would provide these services because they prevent accidents and contribute to home security. However, this would imply the willingness to share data with the company. We have developed the following statements, drawing inspiration from other IoT technologies such as telematics (Śliwiński and Kuryłowicz, 2021) and wearables (Zeier Röschmann et al., 2022). The central elements relate to the perceived value of SH insurance offerings in terms of costs, the value of the insurer’s prevention services, and the respondents’ interest in such SH insurance offerings. Specifically, the statements inquire about the expectation of a discount on the insurance premium (N1), automatic premium adjustments (N2), reimbursement of purchase costs (N3), receiving advice (N4), receiving early warnings (N5), and individual offers from the insurer (N6). The last two statements (N7 and N8) relate to the intention to use SH insurance offerings in the future.

Label	Description	Question
<i>Perceived risks</i>		
Dependence	Concern of increasing dependence on technology	M1.1
Loss of control	Concern of losing control of technology	M1.2
Costs exceeding benefits	Concern of costs exceeding benefits	M2.1
Expensive maintenance	Concern of expensive maintenance	M2.2
Data misuse	Concern of collected data being misused	M3.1
Data used unforeseeable	Concern of collected data being used unforeseeable	M3.2
Overwhelming	Concern of overwhelming technology usage	M4.1
Cumbersome	Concern of cumbersome technology usage	M4.2
Go less out of house	Concern of less going out of the house	M5
Non-essential luxuries	Concern of turning into a non-essential luxury	M6
Source of problems	Concern of leading to problems	M7.1
Insecure	Concern of being insecure	M7.2
Replace contact with others	Concern of replacing contact with others	M8.1
Lack of human interaction	Concern of resulting in lack of human interaction	M8.2
<i>Insurance costs and services</i>		
Discount on insurance premium	Expect to receive discount on insurance premium	N1
Automatic premium adjustment	Expect price of insurance to adjust automatically	N2
Reimbursement of purchase costs	Expect insurer to cover cost of purchase	N3
Advice from insurer	Expect insurer to provide advice on home maintenance	N4
Early warning from insurer	Expect insurer to give early warning on incipient risks	N5
Individual offers from insurer	Expect insurer to provide offers that match personal interests	N6
Future SH insurance intention	Intention to use SH insurance	N7
Future SH insurance plan	Intention to use SH insurance when opportunity arises	N8

Note: All variables are categorical with five levels from *strongly disagree* to *strongly agree*.

Table 3.6: Summary of the variables used in the survey (part 4 of 4).

3.4 Results

In the previous sections, we have presented the development process for the novel data set on SH adoption and summarized the operationalization of the survey. In this section, we present results obtained from the data. First, we examine the key variable related to the intention to adopt an SH, which is discussed in Section 3.4.1. Then, in Section 3.4.2, we examine how different question items relate to the constructs discussed in the literature. In Section 3.4.3, we provide

comprehensive descriptive statistics based on the responses of the $N = 1\,515$ participants in our sample, including their intention to adopt an SH across the main topics covered in our survey. Finally, in Section 3.4.4, we report regression analyses to assess the significance level of the association of various factors with the intention to adopt an SH.

3.4.1 Intention to adopt SH

We measure the intention to adopt an SH using the level of agreement on statements provided in questions O1 to O3. The distribution of the recorded answers is illustrated in Figure 3.2. Considering the answers “agree” and “strongly agree”, we find that 33%, 39%, and 48% express an intention to adopt an SH in the three items. Meanwhile, 37%, 35%, and 32% do not intend using an SH (shares of answers “strongly disagree” and “disagree”).

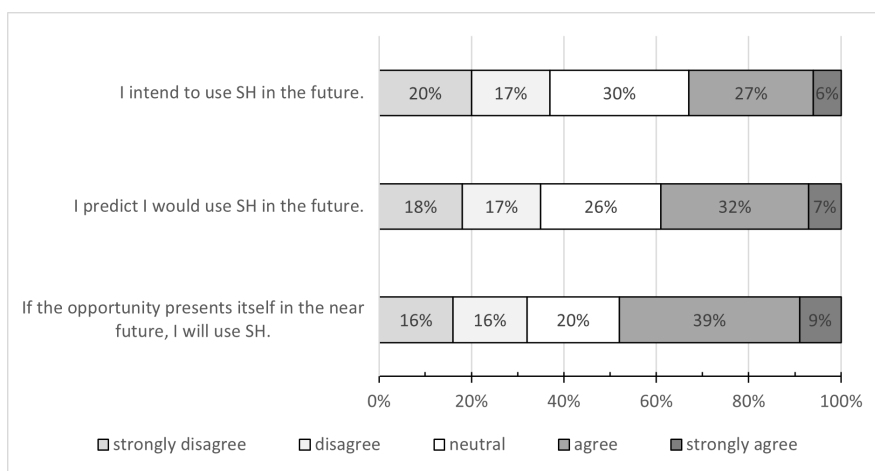


Figure 3.2: Illustration of the responses to the intention-to-adopt SH statements.

To locate the concept of intention to adopt an SH in the following analyses, we use the individual responses to the three statements as measures of the latent construct “intention to adopt SH.” This construct has been validated in previous studies, such as the research conducted by Baudier et al. (2020), and the reliability coefficients in our sample are consistent (Cronbach’s alpha 0.960; see also Section 3.4.2 for all reliability coefficients).

Although the original answers were collected on a five-level Likert scale (“strongly disagree” to “strongly agree”), we code the latent construct into a binary scale using the categories “no” and “yes” to represent the intention to adopt. We operationalize the calculation by assigning numerical values from one to five to the original answers and use the average value of the three statements. A value strictly greater than three is interpreted as a “yes”. We find that 49% of the sample expresses an intention to adopt an SH. In the descriptive statistics provided in Section 3.4.3, we use the construct to represent the proportion of respondents in the “yes” category, providing an indication of the percentage of individuals with an intention to adopt an SH across various respondent characteristics.

3.4.2 Reliability of the constructs

A number of latent constructs derived from the literature were incorporated into the questionnaire. We evaluate their reliability by assessing whether the data align with the hypothesized

constructs. For each construct, we calculate Cronbach’s alpha, a key metric indicating the extent to which the set of items effectively measures the construct. A threshold value of 0.6 is commonly used to determine construct acceptability (Hair et al., 2009; Kreutzer and Wagner, 2013).

Table 3.7 provides an overview of the latent constructs, along with the corresponding questions and Cronbach’s alpha values. We hypothesized a distinct construct for the prevention benefits of comfort, safety, health, and fitness. While all Cronbach’s alphas surpass the designated threshold, we note that the self-developed construct related to fitness exhibits a Cronbach’s alpha of 0.825. It is important to mention that the other constructs have been validated in previous acceptance studies (see, e.g., Chang and Nam (2021)). This also applies to the dimensions of SH adoption, as well as risks and costs in the UTAUT context. While we assess all constructs with our data, we observe high values for Cronbach’s alpha (e.g., for the hedonic motivation, 0.958, and the perceived risks, 0.914). Following evaluation of the constructs’ reliability based on the original five-level Likert scale, we group their values into three categories, “disagree”, “neutral”, and “agree”. Every evaluation on the Likert scale is approximated by a numerical value from one to five. To calculate the construct, we obtain the average score of the values. A mean value below three is coded as “disagree”, a value greater than or equal to three but strictly less than four as “neutral”, and a value greater than or equal to four as “agree”.

Construct	Description	Questions	Cronbach’s α
<i>Evaluation of prevention benefits</i>			
Comfort benefits	Prevention benefits perceived for comfort	G1.1-G1.3	0.699
Safety benefits	Prevention benefits perceived for safety	G2.1-G2.3	0.850
Health benefits	Prevention benefits perceived for health	G3.1-G3.5	0.892
Fitness benefits	Prevention benefits perceived for fitness	G4.1-G4.4	0.825
<i>Dimensions of SH adoption</i>			
Performance expectancy	General SH usage benefits	H1-H6	0.865
Effort expectancy	Easiness of SH usage	I1.1-I4.2	0.953
Facilitating conditions	Support and resources available for SH usage	J1-J8	0.759
Social influences	Relevant extent others believe one should use SH	K1-K4	0.825
Hedonic motivation	Fun or pleasure derived from SH usage	L1-L10	0.958
<i>Risks and costs</i>			
Increased dependence	Risks related to increased dependence	M1.1-M1.2	0.713
Costs	Risks related to costs of purchase and use	M2.1-M2.2	0.871
Privacy	Risks related to privacy	M3.1-M3.2	0.936
Other risks	Risks related to other aspects of daily life	M4.1-M8.2	0.869
Insurance costs	Cost considerations on SH insurance offerings	N1-N3	0.801
Insurance prevention services	Service considerations on SH insurance offerings	N4-N6	0.862
Interest for insurance offering	Intention to use SH insurance offerings	N7-N8	0.847

Note: All constructs are categorical with the three levels *disagree*, *neutral*, and *agree*.

Table 3.7: Summary of the constructs, including underlying questions and loadings.

3.4.3 Descriptive statistics

In the following, we present descriptive results on the survey. Tables 3.8–3.12 display the distribution of respondents across the variables and constructs covered in our survey (see column labeled “Sample”). Additionally, the proportion of respondents who expressed the intention to adopt an SH is provided in column “Intent.”. Results for the constructs (see Table 3.7) are reported on a gray background.

	Sample	Intent.		Sample	Intent.		Sample	Intent.
<i>Knowledge and preference variables</i>								
Knowledge level (A1)			Convenience application (B1)			Health application (B2)		
Poor	60.2	36.3	Dislike	17.5	16.2	Dislike	31.5	26.2
Mediocre	32.2	63.9	Neutral	13.5	21.7	Neutral	22.7	46.1
Good	7.6	86.2	Like	69.0	62.4	Like	45.8	65.8
<i>Socio-demographic variables</i>								
Survey language			Income sufficiency (C2)			Marriage / partnership (C6.1)		
DE	66.6	47.5	Easy	66.5	50.7	Yes	62.3	50.8
FR	33.4	51.9	Difficult	33.5	45.5	No	37.7	45.9
Age (A2)			Expense capacity (C3)			Single household (C6.2)		
45–54 years	31.0	56.3	Yes	66.6	50.8	Yes	30.6	45.6
55–64 years	29.2	50.4	No	33.4	45.2	No	69.4	50.4
65–74 years	30.8	44.5	Professional situation (C4)			Household with kid(s) (C6.4)		
75+ years	9.0	34.2	Employed	49.7	55.5	Yes	22.9	53.5
Gender (A3) ^a			Others	11.0	46.0	No	77.1	47.6
Female	51.0	40.6	Retired	39.3	41.5	Other households (C6.3/5/6)		
Male	49.0	57.7	Home ownership (C5)			Yes	3.8	40.4
Education (C1)			Rent	51.7	46.5	No	96.2	49.3
Mandatory	3.1	43.6	Ownership	48.3	51.6			
High school	64.4	45.5						
Higher education	32.5	56.3						
<i>Active healthy aging variables</i>								
Mildly strenuous activities (D1.1)			Loneliness (D5)			Voluntary work (D6.4)		
Rarely	19.5	46.7	Rarely	86.5	48.0	Rarely	81.0	48.6
Often	80.5	49.5	Often	13.5	55.1	Regularly	8.4	51.0
Really strenuous activities (D1.2)			Cultural activity level (D6.1)			Often	10.6	50.4
Rarely	57.3	46.2	Rarely	72.9	45.1	Club activity level (D6.5)		
Often	42.7	52.6	Regularly	21.5	58.3	Rarely	78.7	47.8
Frailty (D2)			Often	5.6	62.9	Regularly	9.4	50.9
Yes	21.6	47.4	Group sports involvement (D6.2)			Often	11.9	54.7
No	78.4	49.4	Rarely	65.7	47.5	Outing level (D6.6)		
Satisfaction with life (D3)			Regularly	11.1	57.2	Rarely	44.9	42.0
Dissatisfied	5.1	42.2	Often	23.2	49.1	Regularly	38.4	53.2
Neutral	18.9	47.4	Educational courses (D6.3)			Often	16.7	58.0
Satisfied	76.0	49.8	Rarely	87.4	48.5	Active grandparent (D6.7)		
Depressive symptoms (D4)			Regularly	6.0	56.8	Rarely	52.0	47.4
Yes	34.3	50.8	Often	6.6	47.6	Regularly	19.6	51.4
No	65.7	48.0				Often	28.4	50.0
<i>Technology and risk affinity variables</i>								
Technology experimenter (E1)			Technology expert (E3)			Familiarity preferer (E5)		
Disagree	26.8	21.0	Poor	3.2	20.0	Disagree	40.1	58.1
Neutral	23.9	35.1	Good	28.7	34.8	Neutral	25.0	46.1
Agree	49.3	70.9	Excellent	68.1	56.3	Agree	34.9	40.4
Technology pioneer (E2)			Mistake avoider (E4)			Risk-taking level (E6)		
Disagree	53.5	32.7	Disagree	44.2	54.9	Not willing	20.8	36.4
Neutral	21.8	53.5	Neutral	30.0	40.9	Moderately willing	47.3	44.4
Agree	24.7	80.1	Agree	25.8	48.1	Willing	31.9	63.9
<i>Insurance situation variables</i>								
Suppl. health insurance (F1.1)			Liability insurance (F1.4)			Legal expenses insurance (F1.7)		
Yes	76.3	49.5	Yes	92.4	49.5	Yes	55.3	52.8
No	23.7	47.3	No	7.6	42.6	No	44.7	44.2
Motor vehicle insurance (F1.2)			Life insurance (F1.5)			Other insurance (F1.8)		
Yes	80.2	50.5	Yes	26.6	60.0	Yes	5.6	49.3
No	19.8	42.7	No	73.4	44.9	No	94.4	48.9
Travel insurance (F1.3)			Household insurance (F1.6)			Insurance app in use (F2)		
Yes	42.3	53.0	Yes	94.0	49.4	Yes	46.4	60.3
No	57.7	46.0	No	6.0	41.3	No	53.6	39.1

Notes: The column “Sample” reports the sample share per characteristic or answer (sample size $N = 1\,515$); the column “Intent.” reports the share of respondent in each category intending to adopt SH (also see Section 3.4.1). All values are expressed in %. ^a No respondent selected the answer options “diverse” or “prefer not to reply”.

Table 3.8: Descriptive statistics on the variables from parts A to F of the questionnaire.

Knowledge and preference variables. In all three knowledge and preference variables, we have reduced the original five-level answer scale to three levels: “poor”, “mediocre”, and “good”, or, respectively, “dislike”, “neutral”, and “like”. A value of “poor” (or, respectively, “dislike”) reflects the two lower levels of the original scale, “mediocre” (or, respectively, “neutral”) reflects

the middle level, and “good” (or, respectively, “like”) reflects the two upper levels. This simplification reduces the number of categories for analysis and reduces the heterogeneity in the responses while grouping the clearly negative and positive responses.

The results indicate that a higher level of SH knowledge and preference for either of the two applications is linked to a higher intention to adopt an SH. For instance, there is an increase in intention to adopt an SH among those with a mediocre self-assessed knowledge level. Those with a “good” knowledge level have an 86.2% likelihood of being interested in SH technologies. With regard to the two SH applications examined, we find that a preference for either of the two is associated with higher SH interest. Respondents who like the convenience and health SH applications show an increased intention rate of 46.2 and 39.6 percentage points (p.p.), respectively, compared to those who dislike the applications. This finding is in line with the literature (Ayodimeji et al., 2021).

Socio-demographic variables. Variables that reflect a connection to the adoption intention are gender, age, education, and professional situation with male respondents, respondents aged between 45 and 54 years, having higher education, and being employed yielding higher rates. The important difference observed among genders is surprising as such variations have not been documented previously (Shin et al., 2018; Sovacool et al., 2021). Considerable differences are also observed among age groups, with respondents older than 75 years showing a low level of interest compared to others. The adoption rate in terms of the professional situation has not been studied before: we observe differences between those employed and retired, as well as the group “others” consisting of the unemployed, homemakers, and those unable to work. Additionally, living with children in the same household is positively related to interest in an SH.

Active healthy aging variables. The social well-being dimension of the AHA concept (questions D6.1–D6.7) emerges as a prominent element associated with an increased intention to adopt an SH. We grouped the original levels of activities into three categories: “rarely” reflecting the two lower levels (“hardly ever”, “few times a year”), “regularly” the middle level (“1–2× month”), and “often” the two upper levels (“1× week”, “>1× week”). Those who often engage in cultural activities and go out with friends show a higher interest in SHs. Similarly, regular group sports involvement and educational courses are linked to an increased interest. From the dimension of mental well-being, the feeling of loneliness (two levels “rarely” and “often” aggregated from the four original categories) stands in a positive relationship with SH adoption, providing an addition to the existing literature. Meanwhile, other variables such as often engaging in very strenuous physical activity also have a moderate effect.

Technology and risk affinity variables. Overall, our data indicate that technology and risk affinity may be seen as important characteristics of a potential SH user. We reduced all variables within this topic from the original five-level scale to three levels (see also the discussion above). In the variables that measure the level of agreement with a certain statement (E1, E2, E4, and E5), the value “disagree” reflects the two lower levels, “neutral” reflects the middle level, and “agree” reflects the two upper levels. For the technology expertise (E3) and the risk-taking level (E6), the 2-1-2 aggregation logic is the same. In the remainder of this section, the same aggregation is applied for all agreement-related scales.

The greatest positive and negative association with the intention to adopt an SH can be ob-

served in the opposing extremes. Regarding technology affinity, the willingness to experiment (see questions E1 and E2, difference of around 50 p.p. between disagreeing and agreeing subgroups) is more important than technology expertise (E3). For risk affinity, a concept commonly used in insurance studies, the question on risk-taking levels stands out, with rates of 63.9% for those willing to take risks and 36.4% for those who are not.

Insurance situation variables. In the insurance context, being a user of an insurance app is positively linked to SH adoption (60.3% against 39.1%). From the portfolio of existing insurance contracts, the presence of a life insurance policy is particularly notable (60.0% against 44.9%). Furthermore, we note rate increases related to the ownership of a travel or legal expenses insurance.

Evaluation of prevention benefits Referring to Table 3.9, we observe that prevention benefits are perceived in particular within the field of safety. This is evident from the agreement of 71.8% of the respondents and the related high share of adoption intention (57.8%). Concrete prevention measures (see G2.2 and G2.3) are perceived more readily, as indicated by their higher sample share, compared to the abstract promise of safety provided by the technology (G2.1, lower sample share). Additionally, the increase in SH interest regarding safety is relatively small compared to other benefits perceived. Particularly high interest levels can be observed in those individuals that see SHs providing value in terms of health (intention in the construct: 72.5%) and fitness (77.3%). In both fields, control and feedback features tend to be perceived most readily (health monitoring, G3.2, and feedback on exercises, G4.2). Finally, it is worth mentioning that a considerable number of respondents see benefits in checking the health of other family members (G3.5).

Dimensions of SH adoption Table 3.10 presents the dimensions of SH adoption, which were derived from the elements described in Section 3.3.2. Since these dimensions have been studied in the literature, we situate our results therein.

Performance expectancy. Our study aligns with the idea that performance expectancy plays an important role for SH adoption (Marikyan et al., 2019b). A high level is linked to higher SH interest (construct intention: 73.8%). Among the individual items, several aspects stand out. In terms of sample size, the simplification of everyday activities (H1) and the possibility of saving money (H4) are potential benefits expected by the majority. These are followed by home monitoring features (H2).

Effort expectancy. In contrast, the role of effort expectancy appears to be less important. This contradicts, to some extent, the prevailing literature that lists effort expectancy as a key element influencing SH adoption alongside performance expectancy (Baudier et al., 2020; Pal et al., 2018; Tural et al., 2021). However, higher levels of effort expectancy are only moderately associated with increased SH interest (construct intention: 54.2%). Among the individual items, the results confirm these tendencies with no clear differences emerging in the individual aspects.

Facilitating conditions. Perceived facilitating conditions translate into higher SH interest (construct intention: 63.7%). However, a lack of them is associated with the lowest interest levels overall. The relevance of facilitating conditions is a debated topic in the literature. Some studies emphasize the importance of supportive roles, such as concierge (Kim et al., 2017; Pelau

	Sample	Intent.		Sample	Intent.		Sample	Intent.
<i>Comfort benefits</i>								
Burden relief (G1.1)			Value enhancement (G1.3)			Comfort benefits		
Disagree	30.5	37.3	Disagree	19.2	27.7	Disagree	17.8	18.1
Neutral	21.5	37.5	Neutral	33.9	40.6	Neutral	46.5	45.1
Agree	48.0	61.5	Agree	46.9	63.7	Agree	35.7	69.3
Home information (G1.2)								
Disagree	10.7	12.8						
Neutral	14.8	25.1						
Agree	74.5	58.9						
<i>Safety benefits</i>								
Sense of safety (G2.1)			Risk protection (G2.3)			Safety benefits		
Disagree	14.8	17.5	Disagree	7.9	16.3	Disagree	10.8	15.7
Neutral	23.2	37.8	Neutral	12.7	25.5	Neutral	17.4	33.3
Agree	62.0	60.6	Agree	79.4	55.9	Agree	71.8	57.8
Security booster (G2.2)								
Disagree	10.2	16.7						
Neutral	13.9	29.5						
Agree	75.9	56.9						
<i>Health benefits</i>								
Health maintenance (G3.1)			Health encouragement (G3.3)			Family well-check (G3.5)		
Disagree	27.2	27.8	Disagree	32.7	28.6	Disagree	20.4	28.1
Neutral	28.0	43.8	Neutral	30.1	48.5	Neutral	26.9	41.0
Agree	44.8	65.0	Agree	37.2	67.2	Agree	52.7	61.1
Health monitoring (G3.2)			Accident prevention (G3.4)			Health benefits		
Disagree	19.7	23.4	Disagree	30.7	31.2	Disagree	31.0	24.2
Neutral	21.1	37.4	Neutral	31.0	48.7	Neutral	45.2	53.6
Agree	59.2	61.6	Agree	38.3	63.4	Agree	23.8	72.5
<i>Fitness benefits</i>								
Automated fitness (G4.1)			Movement motivation (G4.3)			Fitness benefits		
Disagree	35.1	33.3	Disagree	32.7	30.3	Disagree	41.4	33.1
Neutral	33.9	47.6	Neutral	25.8	44.4	Neutral	43.7	54.2
Agree	31.0	68.1	Agree	41.5	66.5	Agree	14.9	77.3
Exercise feedback (G4.2)			Socializing opportunity (G4.4)					
Disagree	26.3	29.1	Disagree	44.5	40.2			
Neutral	30.4	43.5	Neutral	35.7	49.4			
Agree	43.3	64.8	Agree	29.8	67.8			

Notes: The column “Sample” reports the sample share per characteristic or answer (sample size $N = 1\,515$); the column “Intent.” reports the share of respondent in each category intending to adopt SH (also see Section 3.4.1). All values are expressed in %.

Table 3.9: Descriptive statistics on the evaluation of prevention use cases (part G of the questionnaire).

	Sample	Intent.		Sample	Intent.		Sample	Intent.
<i>Performance expectancy</i>								
Everyday simplification (H1)			Money saving (H4)			Performance expectancy		
Disagree	10.3	8.6	Disagree	10.4	16.3	Disagree	19.3	14.6
Neutral	11.8	17.8	Neutral	16.5	38.5	Neutral	48.1	45.8
Agree	77.9	59.0	Agree	73.1	56.0	Agree	32.6	73.8
Home monitoring (H2)			Social connectivity (H5)					
Disagree	11.7	13.1	Disagree	33.1	34.6			
Neutral	18.9	25.5	Neutral	33.3	47.5			
Agree	69.4	61.1	Agree	33.6	64.5			
Activity motivation (H3)			Shared access (H6)					
Disagree	24.2	26.7	Disagree	23.2	27.9			
Neutral	31.4	42.8	Neutral	23.2	36.8			
Agree	44.4	65.5	Agree	53.6	63.3			

Table 3.10: Descriptive statistics on performance expectancy, effort expectancy, facilitating conditions, social influences, and hedonic motivation (parts H, I, J, K, and L of the questionnaire).

et al., 2021), while others question it (Hoque and Sorwar, 2017; Große-Kreul, 2022). Among the individual items, the results are heterogeneous. In terms of sample size, considerable differences can be found with regard to the preference of the person or institution providing assistance. A large proportion would prefer to rely on professionals (questions J1–J3), while only around one third would turn to family and friends for help (J4–J5).

	Sample	Intent.		Sample	Intent.		Sample	Intent.
<i>Effort expectancy</i>								
Easy to use (I1.1)			Customizable (I2.1)			Autonomous (I4.1)		
Disagree	2.2	18.5	Disagree	3.0	18.9	Disagree	3.7	28.3
Neutral	5.4	28.4	Neutral	7.5	28.0	Neutral	9.6	36.1
Agree	92.4	50.9	Agree	89.5	51.7	Agree	86.7	51.3
Intuitive (I1.2)			Tailored (I2.2)			Seamless (I4.2)		
Disagree	2.2	11.1	Disagree	2.7	14.7	Disagree	2.6	21.9
Neutral	6.5	28.4	Neutral	7.7	33.3	Neutral	5.1	27.0
Agree	91.3	51.3	Agree	89.6	51.4	Agree	92.3	50.9
Easy to learn (I1.3)			Trustworthy (I3.1)			Effort expectancy		
Disagree	3.1	23.1	Disagree	2.5	19.4	Disagree	7.3	19.8
Neutral	6.8	35.7	Neutral	5.2	15.4	Neutral	47.8	48.5
Agree	90.1	50.9	Agree	92.3	51.7	Agree	44.9	54.2
Quickly usable (I1.4)			Warrantied (I3.2)					
Disagree	2.4	13.3	Disagree	3.4	28.6			
Neutral	5.9	30.1	Neutral	8.1	36.6			
Agree	91.7	51.1	Agree	88.5	50.9			
<i>Facilitating conditions</i>								
Availability of usage instructions (J1)			Availability of close people (J4)			Fit to daily life (J7)		
Disagree	3.2	8.2	Disagree	34.1	39.0	Disagree	2.7	11.8
Neutral	8.2	22.8	Neutral	27.5	49.6	Neutral	10.0	25.0
Agree	88.6	52.5	Agree	38.4	57.4	Agree	87.3	52.9
Availability of a professional for questions (J2)			Availability of colleagues/friends (J5)			Fit to household (J8)		
Disagree	5.1	42.9	Disagree	26.9	35.9	Disagree	4.4	10.9
Neutral	10.9	44.4	Neutral	35.7	46.3	Neutral	11.2	27.3
Agree	84.0	49.9	Agree	37.4	60.9	Agree	84.4	53.8
Availability of a professional when problems (J3)			Availability of own knowledge (J6)			Facilitating conditions		
Disagree	4.1	27.5	Disagree	24.8	23.5	Disagree	5.8	6.9
Neutral	6.8	36.9	Neutral	18.9	38.0	Neutral	47.3	39.5
Agree	89.1	50.9	Agree	56.3	63.8	Agree	46.9	63.7
<i>Social influences</i>								
Meaning to important others (K1)			Prestigious image (K3)			Social influences		
Disagree	25.3	27.7	Disagree	41.1	36.1	Disagree	42.5	29.4
Neutral	55.1	48.0	Neutral	40.9	50.3	Neutral	47.7	59.0
Agree	19.6	79.0	Agree	18.0	75.3	Agree	9.8	85.1
Meaning to opinion makers (K2)			Modern image (K4)					
Disagree	36.7	29.7	Disagree	16.7	23.7			
Neutral	47.3	53.9	Neutral	32.8	41.0			
Agree	16.0	78.4	Agree	50.5	62.5			
<i>Hedonic motivation</i>								
Entertaining (L1)			Versatile (L5)			Trending (L9)		
Disagree	23.0	18.6	Disagree	14.8	15.2	Disagree	17.8	18.1
Neutral	33.1	40.2	Neutral	36.5	39.2	Neutral	28.0	39.2
Agree	43.9	71.4	Agree	48.7	66.6	Agree	54.2	64.1
Enjoyable (L2)			Fun (L6)			Variegating (L10)		
Disagree	22.6	12.1	Disagree	18.9	17.1	Disagree	27.6	25.7
Neutral	32.3	38.2	Neutral	32.6	35.6	Neutral	35.9	46.4
Agree	45.1	75.1	Agree	48.5	70.4	Agree	36.5	69.0
Convenient (L3)			Pleasant (L7)			Hedonic motivation		
Disagree	9.8	8.3	Disagree	18.7	5.2	Disagree	22.9	8.5
Neutral	21.9	24.3	Neutral	22.9	23.9	Neutral	47.7	48.1
Agree	68.3	62.7	Agree	58.4	72.8	Agree	29.4	81.9
Curiosity-inducing (L4)			Relieving (L8)					
Disagree	16.9	6.2	Disagree	10.9	6.7			
Neutral	18.9	22.6	Neutral	21.5	20.2			
Agree	64.2	68.0	Agree	67.6	64.9			

Notes: See Table 3.9.

Table 3.10: *Cont.*

Social influences. Our data indicate meaningful social influences. When others encourage SH usage, respondents' intention to adopt an SH is among the highest (85.1%). While the literature lacks a clear consensus on this matter, few studies suggest relatively little relevance (Cimperman et al., 2016; Pal et al., 2018). In terms of sample size among the individual items, our results suggest that it is rather the influence of strong opinion makers (K1–K2) and less the image attached to the technology (K3–K4) that prevail.

Hedonic motivation. The data suggest likewise importance of perceived enjoyment and fun of using an SH. When hedonic motivators are present, SH interest tends to be very high, yielding an adoption rate of 81.9%. Moreover, a lack of such motivation is linked to very low interest levels. Therefore, perceived enjoyment associated with SH usage seems to emerge as a central element for generating interest, which is in line with recent evidence (Große-Kreul, 2022; Sequeiros et al., 2021). These patterns remain consistent among the individual items. In terms of sample size, we find indications that the majority associates SH usage with feelings of relief (arguments L3, L7, and L8) and curiosity (L4).

Risks and costs Tables 3.11 and 3.12 present different facets of risks and barriers associated with SHs, as well as how insurance variables are linked to interest in SH technologies.

	Sample	Intent.		Sample	Intent.		Sample	Intent.
<i>Increased dependence</i>								
Dependence (M1.1)			Loss of control (M1.2)			Increased dependence		
Disagree	42.7	54.1	Disagree	45.6	58.7	Disagree	46.2	56.4
Neutral	23.0	49.1	Neutral	23.0	41.8	Neutral	32.4	44.8
Agree	34.3	42.5	Agree	31.4	40.1	Agree	21.4	39.2
<i>Costs</i>								
Costs exceeding benefits. (M2.1)			Expensive maintenance (M2.2)			Costs		
Disagree	16.4	76.4	Disagree	12.2	73.5	Disagree	14.8	75.5
Neutral	23.8	57.3	Neutral	19.3	49.4	Neutral	28.2	55.9
Agree	59.8	38.1	Agree	68.5	44.5	Agree	57.0	38.6
<i>Privacy</i>								
Data misuse (M3.1)			Data used unforeseeable (M3.2)			Privacy		
Disagree	17.5	63.9	Disagree	16.1	61.3	Disagree	17.9	62.6
Neutral	18.3	56.8	Neutral	16.5	56.1	Neutral	20.5	57.1
Agree	64.2	42.7	Agree	67.4	44.3	Agree	61.6	42.3
<i>Other risks</i>								
Overwhelming (M4.1)			Non-essential luxuries (M6)			Replace contact with others (M8.1)		
Disagree	51.8	59.7	Disagree	29.6	76.3	Disagree	59.0	55.5
Neutral	21.5	36.3	Neutral	24.3	52.8	Neutral	22.4	42.6
Agree	26.7	38.4	Agree	46.1	29.4	Agree	18.6	35.9
Cumbersome (M4.2)			Source of problems (M7.1)			Lack of human interaction (M8.2)		
Disagree	36.9	62.7	Disagree	25.7	69.9	Disagree	54.8	57.7
Neutral	26.6	47.3	Neutral	29.4	51.6	Neutral	22.1	43.4
Agree	36.5	36.3	Agree	44.9	35.4	Agree	23.1	33.4
Go less out of house (M5)			Insecure (M7.2)			Other risks		
Disagree	67.1	54.7	Disagree	27.1	67.0	Disagree	56.5	61.1
Neutral	22.5	36.9	Neutral	26.5	52.0	Neutral	34.7	34.8
Agree	10.4	38.0	Agree	46.4	36.7	Agree	8.8	25.7

Notes: See Table 3.9.

Table 3.11: Descriptive statistics on perceived risks (part M of the questionnaire).

Perceived risks. The higher the perceived risks, the lower the interest in SHs. Among the risks examined, costs considerations stand out, corresponding to an adoption rate of 38.6% at the construct level. This finding contradicts the prevailing literature, which tends to downplay their importance (Sovacool and Furszyfer Del Rio, 2020; Wang et al., 2020). Furthermore, we observe that privacy risks, while attracting attention, have a less negative association (construct intention: 42.3%) than suggested by the literature (Marikyan et al., 2019b). In comparison to cost considerations or risks related to increased dependence, privacy concerns seem less salient. Other risks that have not been extensively studied in earlier research are also perceived. Although these risks are reported less frequently (8.8%), they clearly reflect a negative association with interest in SHs. Overall, we observe that perceived risks stand in a negative relationship to SH adoption intention, but their relevance seems to be lower when compared to the consequences of low facilitating conditions or low hedonic motivation.

	Sample	Intent.		Sample	Intent.		Sample	Intent.
<i>Insurance costs</i>								
Discount on insurance premium (N1)			Reimbursement of purchase costs (N3)			Insurance costs		
Disagree	11.5	23.8	Disagree	22.4	40.6	Disagree	20.7	31.6
Neutral	24.2	38.7	Neutral	27.2	43.0	Neutral	39.4	46.8
Agree	64.3	57.3	Agree	50.4	55.8	Agree	39.9	60.0
Automatic premium adjustment (N2)								
Disagree	18.2	32.0						
Neutral	29.5	39.9						
Agree	52.3	59.9						
<i>Insurance prevention services</i>								
Advice from insurer (N4)			Individual offers from insurer (N6)			Insurance prevention services		
Disagree	18.0	26.5	Disagree	22.6	37.5	Disagree	23.1	31.7
Neutral	26.8	35.8	Neutral	25.9	36.6	Neutral	38.8	43.7
Agree	55.2	62.6	Agree	51.5	60.2	Agree	38.1	64.8
Early warning from insurer (N5)								
Disagree	20.7	34.6						
Neutral	29.8	40.8						
Agree	49.5	59.9						
<i>Interest for insurance offering</i>								
Future SH insurance intention (N7)			Future SH insurance plan (N8)			Interest for insurance offering		
Disagree	28.2	23.4	Disagree	31.3	16.0	Disagree	35.3	22.5
Neutral	37.5	47.5	Neutral	34.3	44.5	Neutral	37.8	49.5
Agree	34.3	71.5	Agree	34.4	83.4	Agree	26.9	82.5

Notes: See Table 3.9.

Table 3.12: Descriptive statistics on insurance costs and services (part N of the questionnaire).

Insurance costs and services. Cost aspects of a potential insurance offering appear to have a limited link to SH interest (construct intention: 60.0%). The link between the perceived value of insurance services related to prevention and SH interest is stronger (64.8%). This observation is noteworthy for SHs, as financial rewards have been found to be more important than service aspects in other IoT insurance areas (e.g., telematics and wearables Śliwiński and Kuryłowicz (2021); Wiegard and Breitner (2019)). Finally, we note that those interested in an SH insurance offering reflect a clearly higher intention to adopt SHs (82.5%). This value increases by 60 p.p. when compared to those who show no interest in obtaining such insurance.

3.4.4 Regression analysis

Building upon the binary variable definition regarding the intention to adopt an SH (Section 3.4.1), and extending the descriptive statistics presented above (Section 3.4.3), we propose to perform regression analyses. These analyses assist in identifying the relevant relationships and the significance of the associations between the intention to adopt an SH and the studied variables. The modeling results supplement the previous descriptive statistics. We follow the identical procedure for simplifying the scale as detailed in the previous section and apply the specified categories to all variables examined. We distinguish three sets of variables. First, we consider the set of variables related to SH service and prevention areas (parts G to N of the questionnaire), which we have grouped into 16 constructs (see Table 3.7 in Section 3.4.2). Second, we concentrate on the 13 AHA variables among the user characteristics (part D of the questionnaire). Third, we consider all other characteristics explained by 30 variables (parts A to C and E to F of the questionnaire).

For each of the three variable sets, we build a generalized linear regression model for the response variable “intention to adopt SH,” which responds to the estimation of the following equation

through all responses i :

$$g(\text{intention to adopt SH}_i) = \beta_0 + \sum_{\mathbf{X} \in \mathcal{V}} \beta_{\mathbf{X}} \mathbf{X}_i + \epsilon_i,$$

where $g(\cdot)$ denotes the link function, β_0 the base coefficient (intercept), and $\beta_{\mathbf{X}}$ the vector of coefficients estimated for the non-baseline categories of each variable \mathbf{X} in \mathcal{V} , where \mathcal{V} is the set of variables included in the model. ϵ_i is the error term. For each survey response, $\beta_{\mathbf{X}}$ and \mathbf{X}_i are vectors of dimension $c_{\mathbf{X}} - 1$, where $c_{\mathbf{X}}$ is the number of categories in \mathbf{X} .

Using Akaike’s information criterion (AIC), we find that the logit link function fits the models slightly better than the probit link function. Therefore, we select the logit link function for g . The results of the analyses using the three full sets of variables are reported in Tables 3.16–3.18 in Appendix 3.7. To identify the primary drivers of the response, a forward and backward stepwise selection algorithm based on the AIC measure is employed. We derive reduced models, retaining only those variables that improve the models. Using the logit link function, the reduced models contain eight, four, and twelve variables, respectively. We report the results, including the relevant variables, coefficients, and significance levels, in Tables 3.13–3.15.

	β -estimate	p -value	Sig.
Intercept	−2.743	<0.001	***
Health benefits (G3.1–G3.5, baseline: disagree)			
Neutral	0.410	0.026	*
Agree	0.265	0.257	
Facilitating conditions (J1–J8, baseline: disagree)			
Neutral	1.316	0.016	*
Agree	1.406	0.011	*
Social influences (K1–K4, baseline: disagree)			
Neutral	0.330	0.045	*
Agree	0.581	0.084	.
Hedonic motivation (L1–L10, baseline: disagree)			
Neutral	1.331	<0.001	***
Agree	2.375	<0.001	***
Costs (M2.1–M2.2, baseline: disagree)			
Neutral	−0.692	0.009	**
Agree	−0.945	<0.001	***
Other risks (M4.1–M8.2, baseline: disagree)			
Neutral	−0.689	<0.001	***
Agree	−0.946	0.002	**
Insurance prevention services (N4–N6, baseline: disagree)			
Neutral	−0.273	0.186	
Agree	0.055	0.802	
Interest for insurance offering (N7–N8, baseline: disagree)			
Neutral	0.647	<0.001	***
Agree	1.726	<0.001	***

Note: the significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.13: Results of the reduced logit regression using selected constructs (parts G to N of the questionnaire).

When examining the set of variables related to SH services and prevention, both hedonic motivation and interest in SH insurance offerings emerge as highly significant factors (see Table 3.13). The former highlights the important role of enjoyment in promoting SH adoption. In addition, facilitating conditions and social influences also have a notable impact on SH adoption, highlighting the importance of accessible support and peer influences. The health benefits illustrate the important role of health-related factors in our SH study. Conversely, cost-related and other risk factors pose significant challenges as barriers to SH adoption.

	β -estimate	p-value	Sig.
Intercept	-0.457	<0.001	***
Really strenuous activities (D1.2, baseline: rarely)			
Often	0.170	0.146	
Loneliness (D5, baseline: rarely)			
Often	0.308	0.067	.
Cultural activity level (D6.1, baseline: rarely)			
Regularly	0.386	0.009	**
Often	0.431	0.100	
Outing level (D6.6, baseline: rarely)			
Regularly	0.342	0.008	**
Often	0.443	0.012	*

Note: the significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.14: Results of the reduced logit regression using selected active healthy aging variables (part D of the questionnaire).

Regarding AHA, the physical, mental, and social dimensions are all important in shaping SH adoption (see Table 3.14). In particular, engagement in social activities, especially those involving higher levels of going out with friends and cultural activities, have significant effects. Although less prominent, both loneliness and physical activity also contribute to higher SH interest, representing the mental and physical dimensions of AHA, respectively.

Among the other factors related to personal characteristics, knowledge and preference-related variables are identified as significant drivers of SH interest (see Table 3.15). The knowledge variable has a significant effect even at the medium categorical level (“mediocre”). In addition, factors related to technology and risk affinity play an important role in promoting the adoption of an SH. Specifically, variables related to technology experimentation are a key component. Gender is also significant, as males show a greater interest in SHs. Furthermore, an individual’s intention to adopt is influenced by additional socio-demographic factors such as age, home ownership, marital status, and life insurance ownership.

3.5 Discussion and implications

In this research, we have examined SH adoption and considered the value of SH technologies in active aging and prevention. Within the prevention context, safety aspects receive the highest level of agreement, suggesting that safety could serve as a door opener for promoting adoption. The positive relationship between prevention-related benefits and interest in SHs holds for all benefits examined. Notably, it is particularly pronounced for fitness and health. From the

	β -estimate	p -value	Sig.
Intercept	-2.834	<0.001	***
Knowledge level (A1, baseline: poor)			
Mediocre	0.609	<0.001	***
Good	1.274	0.001	***
Convenience application (B1, baseline: dislike)			
Neutral	-0.055	0.855	
Like	1.360	<0.001	***
Health application (B2, baseline: dislike)			
Neutral	0.606	0.003	**
Like	1.228	<0.001	***
Age (A2, baseline: 45–54 years)			
55–64 years	-0.412	0.029	*
65–74 years	-0.389	0.048	*
75+ years	-0.620	0.028	*
Gender (A3, baseline: female)			
Male	0.409	0.006	**
Home ownership (C5, baseline: rent)			
Ownership	0.394	0.012	*
Marriage / partnership (C6.1, baseline: no)			
Yes	-0.234	0.144	
Technology experimenter (E1, baseline: disagree)			
Neutral	0.295	0.165	
Agree	1.255	<0.001	***
Technology pioneer (E2, baseline: disagree)			
Neutral	0.225	0.244	
Agree	0.790	<0.001	***
Mistake avoider (E4, baseline: disagree)			
Neutral	-0.102	0.568	
Agree	0.465	0.015	*
Familiarity preferer (E5, baseline: disagree)			
Neutral	-0.361	0.057	.
Agree	-0.407	0.023	*
Life insurance (F1.5, baseline: Yes)			
No	0.401	0.022	*

Note: the significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.15: Results of the reduced logit regression using selected variables with all other personal characteristics (parts A to C and E to F of the questionnaire).

regression analyses, we learn that health-related benefits in particular have a significant impact on older adults' intention to adopt an SH and are therefore particularly important in our SH context.

Second, we find that the integration of the AHA concept proves valuable. The AHA concept provides relevant parameters for future characterizations of older individuals with an interest in SHs. In this context, we observe that socially engaged individuals show higher levels of interest in SH technologies. Although at a lower level compared to other socio-demographic variables, the physical and mental dimensions of the AHA concept can also potentially be used for characterization (e.g., high physical activity and reported loneliness). The AHA parameters provide a positive and active view of the aging process. They also suggest that individuals who

age actively tend to have higher rates of adoption of SHs. Therefore, it can be argued that SHs may be associated with an active and healthy lifestyle.

Third, we point to additional characteristics of potential SH users aged 45 and older: knowledge level, technology affinity, and risk affinity. The latter has not been previously discussed as a variable for SH adoption. In addition, we find typical socio-demographic variables that are further associated with a higher SH interest. Gender, age, home ownership, marital status, and ownership of life insurance policies are the most relevant. Gender differences are particularly pronounced, which has only been observed in another study (Sovacool et al., 2021). This raises the question as to whether certain SH service areas are gendered among older adults, possibly influenced by (Swiss) cultural aspects (Tural et al., 2021). Furthermore, we observe that the influence of age does not seem to be as strong as suggested by existing research.

Fourth, we contribute to the literature by examining the factors influencing SH adoption by reflecting on these relationships and providing initial evidence on understudied elements. Our findings suggest a strong relationship between the fun and enjoyment associated with the technology and higher adoption intentions. Older individuals who expect to enjoy using SHs express higher levels of interest, while those who do not expect to enjoy it report no interest. The literature also recognizes the importance of hedonic motivators for SH use (Sequeiros et al., 2021), an aspect that has only recently been systematically addressed in academic studies (Marikyan et al., 2019a). Additionally, we observe that perceived risks are associated with lower SH interest. In particular, perceived risks related to costs and emerging aspects of SH technology seem to play a role in this context, which is in line with Pal et al. (2018). In contrast, privacy concerns appear to have less influence than previously described by Hubert et al. (2019). Finally, under the assumption of an SH-based insurance offer, we find a positive relationship between higher adoption intention and interest in preventative insurance services as well as overall interest in SH insurance.

3.6 Conclusions, limitations, and future research

SH technologies aim to improve the quality of life at home by providing various services related to the area of energy, health, safety, and comfort. Changing demographics combined with a preference to age at home and increasing digital affinity are some of the aspects that invite one to study the adoption of SH among older individuals. The existing literature primarily takes a disease-centered approach to aging. The value of an SH as an enabler of active and healthy aging based on prevention paradigms has not yet been explored. We contribute to filling this gap by developing a survey that integrates AHA variables and prevention benefits related to daily life at home. Our results strongly suggest that most older adults recognize the preventive benefits of SHs, especially in the areas of safety and health. Adoption intention varies based on user characteristics such as knowledge, technology and risk affinity, and gender. By integrating parameters related to AHA, we connect social engagement and hedonic motivators to increased interest in the technology. Cost and other barriers to SH interest are also examined. Overall, this paper presents a novel approach to studying SH adoption among older adults by integrating previously unstudied AHA parameters and preventive benefits. Our main contribution is promoting a positive perception of SHs as a valuable tool for enabling a proactive lifestyle to prevent risks among aging individuals. Unlike previous studies that often focus on support systems for frailty in old age, we expand the narrative beyond the traditional view of SHs as

reactive solutions for aging-related challenges. Hence, while validating established drivers, our approach offers a first look at the relative importance of previously unstudied factors that contribute to the interest in using SHs.

Although our results are preliminary, they form the foundational backbone for future research in this area. An important avenue would be to validate the importance of our findings in actively aging individuals via comprehensive econometric analyses, such as structural equation modeling. These models could help to elucidate the factors behind the uptake of SH technologies, and enable the development of detailed profiles of potential older adopters. Future research may also benefit from the inclusion of qualitative methods, such as focus group discussions, to gain a richer understanding of the underlying nuances and dynamics of specific factors of interest in the context of aging. Altogether, this research facilitates future analyses to assess the significance of prevention in SHs. Our findings indicate a considerable importance of safety- and health-related factors while emphasizing the most readily perceived risks. The ability to identify and compute risks is a fundamental aspect in the development of effective prevention strategies. Our work can establish the groundwork for future research that concentrates on designing risk assessment techniques suitable to a technological context and can serve as a starting point for improving safety in the home through the use of SHs.

While our study aims to fill an important research gap, it is imperative to acknowledge its limitations. The susceptibility of our data to biases such as self-report and social desirability could impact their accuracy and reliability. Additionally, since the survey was administered only once, the absence of a temporal dimension in our research restricts our ability to establish causal relationships rather than just associations. In addition, our analysis solely concentrates on Switzerland. Although some discoveries might be relevant to other European countries with similar socioeconomic characteristics, our results cannot be directly generalized to a global context.

3.7 Appendix

Appendix A: Questionnaire

Part A: Introduction

A “smart home” is a connected and intelligent home. Examples of smart homes are home systems with temperature controllers, door sensors, lighting systems, robotic vacuum cleaners, or even fitness exercises on the TV or video consultation with a doctor. Typically, a smart home is digital and can often be controlled remotely via a mobile phone.

With the following survey, we investigate the interest for different smart home systems. Specifically, questions regarding benefits, design and risks are asked.

A1: Knowledge level. Which best describes your knowledge of smart home?

Answer options: five levels from no knowledge to very good knowledge.

A2: Age. Please state your exact age. *Numeric answer.*

A3: Gender. Please state your gender.

Answer options: female; male; diverse; prefer not to reply.

Part B: Smart home scenario

In the following you will find a smart home scenario based on two examples.

Sensors in the housing



Allow to control the home at any time via mobile phone and display specific information (e.g., humidity or unusual activities).

Mobile health device



Simplifies the control of one's own health status and the communication with healthcare organizations (e.g., routine checkups or consultation hours).

Note: The above visualization is used from this point on throughout the survey, pinned on the top of the screen.

Example 1: Sensors in the housing. Sensors can already detect power consumption, temperature and humidity as well as movements. They are permanently on and can be controlled in real time via mobile phone. This makes it easy to adjust the room climate, control power consumption, alert for dangers such as a break-in, or allow access to neighbors when one is absent.

Example 2: Mobile health devices. They are compact devices, similar in size to a tablet, that enable health monitoring through integrated cameras and measuring devices. These devices are activated only when necessary, providing access to new health services. Fitness assessments and routine examinations can be conducted from the comfort of one's home, while spontaneous inquiries can be addressed through video calls.

B1: Convenience application. How do you like the “sensors in the housing” example?

Answer options: five levels from dislike to like.

B2: Health application. How do you like the “mobile health devices” example?

Answer options: five levels from dislike to like.

Part C: Socio-demographic profile

C1: Education. Please indicate your highest professional or higher education.

Answer options: mandatory school; high school or professional education; higher education.

C2: Income sufficiency. Thinking of your household’s total monthly income, would you say that your household is able to make ends meet...?

Answer options: with great difficulty; with some difficulty; fairly easily; easily.

C3: Expense capacity. Could your household afford to pay an unexpected expense of CHF 2’400 without borrowing any money?

Answer options: yes; no.

C4: Professional situation. Which of the following options best describes your current employment situation?

Answer options: retired; employed/part-time employed or self-employed (including in the family business); unemployed; homemaker; permanently unable to work due to illness or disability.

C5: Home ownership. Do you live in a rental or owned property? Indicate cooperative housing as rent.

Answer options: rent; ownership.

C6: Household situation. Who lives in your household? Please select all applicable options.

- **C6.1: Marriage/partnership.** Spouse or partner
- **C6.2: Single household.** Live alone
- **C6.3: Other household.** Roommate
- **C6.4: Household with kids.** Children
- **C6.5: Other household.** Grandchildren
- **C6.6: Other household.** Parents

Answer options for each household composition: yes; no.

Part D: Active healthy aging

D1.1: Mildly strenuous activities. How often do you perform activities that are mildly strenuous (e.g., light gardening, washing the car or going for a walk)?

Answer options: hardly ever; once to twice per month; once per week; more than once a week.

D1.2: Really strenuous activities. How often do you perform activities that are really strenuous (e.g., fitness group classes like Zumba, jogging/running, intense strength or endurance training, heavy gardening)?

Answer options: hardly ever; once to twice per month; once per week; more than once a week.

D2: Frailty. Please indicate whether you have any difficulty doing one of the following everyday activities: getting up from a chair after sitting for long periods, lifting or carrying a heavy bag of groceries, picking up a small coin from a table. (Exclude any difficulties that you expect to last less than three months.)

Answer options: yes; no.

D3: Satisfaction with life. On a scale from “1” to “5” where “1” means completely dissatisfied and “5” means completely satisfied, how satisfied are you with your life?

Answer options: five levels from 1 to 5.

D4: Depressive symptoms. In the last month, have you been sad or depressed? (Clarification: by sad or depressed, we mean miserable, in low spirits, or blue.)

Answer options: yes; no.

D5: Loneliness. How much of the time do you feel you lack companionship?

Answer options: almost never/never; once to twice per month; once a week; more than once a week.

D6: Social well-being. Which of the following activities have you done how often in the past twelve months?

- **D6.1: Cultural activity level.**
Cultural activities with friends or like-minded people (theater visits, city trips, etc.)
- **D6.2: Group sports involvement.**
Group sports activities (fitness group classes, hikes, bike tours, etc.)
- **D6.3: Educational courses.**
Attendance of an educational or training course
- **D6.4: Voluntary work.**
Voluntary or charity work
- **D6.5: Club activity level.**
Participation in club activities (local hometown club, sports club, etc.)
- **D6.6: Outing level.**
Going out with friends (dinners, cooking evenings, etc.)
- **D6.7: Active grandparent.**
Helping others (looking after grandchildren, caring for relatives, etc.)

Answer options for each activity type: hardly ever; few times per year; once to twice per month; once per week; more than once a week.

Part E: Technology and risk affinity

Please state your level of agreement with the following statements.

E1: Technology experimenter.

If I heard about a new information technology, I would look for ways to experiment with it.

Answer options: five levels from strongly disagree to strongly agree.

E2: Technology pioneer.

Among my peers, I am usually the first to explore new information technologies.

Answer options: five levels from strongly disagree to strongly agree.

E3: Technology expert.

How would you rate your skills using a smartphone or tablet?

Answer options: poor (I have never used one); fair; good; very good; excellent.

E4: Mistake avoider.

If I could possibly make a mistake with a new product, I don't use it.

Answer options: five levels from strongly disagree to strongly agree.

E5: Familiarity preferer.

I prefer to visit places where I know what I'm getting rather than trying new things (e.g., going to the hairdresser, restaurants in my area, or hotels on vacation).

Answer options: five levels from strongly disagree to strongly agree.

E6: Risk-taking level.

How do you see yourself personally: Are you generally a risk-taker or do you try to avoid risks? ("1" = not at all willing to take risks; "5" = very willing to take risks.)

Answer options: five levels from 1 to 5.

Part F: Insurance situation

F1: Insurance portfolio. Which of the following insurance products do you have?

- **F1.1: Suppl. health insurance** Supplementary health insurance (in addition to mandatory health insurance)
- **F1.2: Motor vehicle insurance** Motor vehicle insurance
- **F1.3: Travel insurance** Travel insurance
- **F1.4: Liability insurance** Liability insurance
- **F1.5: Life insurance** Life insurance
- **F1.6: Household insurance** Household insurance
- **F1.7: Legal expenses insurance** Legal expenses insurance
- **F1.8: Other insurance** Other: [*Free text as answer option.*]

Answer options for each insurance type: yes; no.

F2: Insurance app in use.

Do you use an app from your insurance company?

Answer options: yes; no.

Part G: Evaluation of prevention benefits

I expect smart home to be useful, ...

G1.1: Burden relief.

... to reduce my burden of certain household activities (e.g., cleaning or maintaining household).

G1.2: Home information.

... because it provides me with valuable information and control options about the state of my home (e.g., which appliances are on/off).

G1.3: Value enhancement.

... because it contributes to maintaining or increasing the value of my property.

G2.1: Sense of safety.

... because it makes me feel safe.

G2.2: Security booster.

... because it increases my home security (e.g., burglary).

G2.3: Risk protection.

... because it protects me against certain risks at home (e.g., fire or gas).

G3.1: Health maintenance.

... because it allows me to take better care of my health and thus avoid a visit to the doctor.

G3.2: Health monitoring.

... because it allows me to easily monitor my health metrics (e.g., daily activity or blood pressure).

G3.3: Health encouragement.

... because it motivates me to behave healthier (e.g., watch less TV or go to bed earlier).

G3.4: Accident prevention.

... because it can help to prevent accidents (such as falls) or other health risks.

G3.5: Family well-check.

... because I can check if family and friends are doing well (e.g., notification if a person falls at home).

G4.1: Automated fitness.

... because I automatically do something for my fitness.

G4.2: Exercise feedback.

... because I get immediate feedback on fitness exercises that I can do on my own at home.

G4.3: Movement motivation.

... because it motivates me to move about more.

G4.4: Socializing opportunity.

... because it allows me to meet new people (e.g., for training groups or competitions).

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part H: Performance expectancy

I expect smart home to be useful, ...

H1: Everyday simplification.

... because it simplifies everyday life.

H2: Home monitoring.

... because it allows me to monitor state or progress effectively.

H3: Activity motivation.

... because it can motivate me to do certain activities that I otherwise don't like to do.

H4: Money saving.

... because I save money with it (e.g., on heating/electricity costs or healthcare expenses).

H5: Social connectivity.

... because it allows me to stay in touch with family and friends.

H6: Shared access.

... because I could give access to others when needed (e.g., to a neighbor when I'm away on vacation or to my primary care physician to send health data).

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part I: Effort expectancy

It is *very* important that smart home ...

I1.1: Easy to use.

... is easy to use.

I1.2: Intuitive.

... is intuitively understandable.

I1.3: Easy to learn.

... is easy for me to learn.

I1.4: Quickly usable.

... is designed in such a way that I can get it right quickly.

I2.1: Customizable.

... allows me to customize for myself.

I2.2: Tailored.

... is tailored to me with appropriate content and functions.

I3.1: Trustworthy.

... is trustworthy.

I3.2: Warrantied.

... is backed by warranties from credible manufacturers.

I4.1: Autonomous.

... is usable without consulting others (friends or experts).

I4.2: Seamless.

... can be used independently and without major problems.

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part J: Facilitating conditions

With regard to my capabilities, ...

J1: Availability of usage instructions.

... I assume that instructions on how to properly use smart home will be available.

J2: Availability of a professional for questions.

... I should be able to contact a professional if I have any questions.

J3: Availability of a professional when problems.

... I assume that a professional will be available to help with system problems.

J4: Availability of close people.

... I can turn to people around me if I have difficulties using smart home.

J5: Availability of colleagues/friends.

... I assume that colleagues or friends will be happy to support me in how to use smart home.

J6: Availability of own knowledge.

... I have the knowledge required to use a smart home.

J7: Fit to daily life.

... it is very important that smart home fits well into my daily life today.

J8: Fit to household.

... it is very important that smart home fits well with the way I organize my household (apartment/house).

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part K: Social influences

Please state your level of agreement with the following statements.

K1: Meaning to important others.

People that are important to me think that I should use smart home more.

K2: Meaning to opinion makers.

People whose opinions I value prefer that I use smart home.

K3: Prestigious image.

People who use smart home have a more prestigious image than people who do not.

K4: Modern image.

People who use smart home are modern.

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part L: Hedonic motivation

I think using smart home ...

L1: Entertaining.

... is entertaining.

L2: Enjoyable.

... would be enjoyed by me.

L3: Convenient.

... is convenient.

L4: Curiosity-inducing.

... arouses my curiosity.

L5: Versatile.

... is versatile.

L6: Fun.

... is fun.

L7: Pleasant.

... would please me.

L8: Relieving.

... brings me relief.

L9: Trending.

... helps me to be at the pulse of time.

L10: Variegating.

... leads to more variety in everyday life.

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part M: Perceived risks

I have concerns ...

M1.1: Dependence.

... about becoming dependent on technology and how it works.

M1.2: Loss of control.

... that I can't control a smart home on my own and could lose control.

M2.1: Costs exceeding benefits.

... that the costs might exceed the benefits.

M2.2: Expensive maintenance.

... that smart home could be expensive to purchase and maintain.

M3.1: Data misuse.

... that information collected from smart home, could be misused.

M3.2: Data used unforeseeable.

... that the information I disclose could be used in a way I cannot foresee.

M4.1: Overwhelming.

... that using smart home might overwhelm me.

M4.2: Cumbersome.

... that using smart home could be cumbersome.

M5: Go less out of house.

... that I might get out of the house less when living in a smart home.

M6: Non-essential luxuries.

... that smart home could be a non-essential luxuries.

M7.1: Source of problems.

... that the use of smart home could lead to problems.

M7.2: Insecure.

... that a smart home could be insecure.

M8.1: Replace contact with others.

... that using smart home could replace contact with others (e.g., family or friends).

M8.2: Lack of human interaction.

... that the use of smart home could result in a lack of human interaction.

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part N: Insurance costs and services

Suppose you could get smart home services from an insurance company. The insurance company provides such services because they prevent accidents and contribute to home security. However, this implies a willingness to share data with the company. In the case of a smart home insurance offering, ...

N1: Discount on insurance premium.

... I would expect to receive a discount on the insurance premium (e.g., on homeowner's or health insurance).

N2: Automatic premium adjustment.

... I would expect the price of the insurance to adjust automatically (e.g., if during the vacations the lights simulate home presence).

N3: Reimbursement of purchase costs.

... I would expect the insurance company to cover the cost of purchasing the smart home device.

N4: Advice from insurer.

... I would expect the insurance company to provide me with information and advice on how to make my home safer, better, and healthier to live in.

N5: Early warning from insurer.

... I would expect the insurance company to give me early warning regarding incipient risks (e.g., open garage, water damage, or lack of exercise).

N6: Individual offers from insurer.

... I would expect the insurance company to provide me with offers that match my interests (e.g., discount on humidifiers due to room temperature or energy-saving light bulbs due to electricity consumption).

N7: Future smart home insurance intention.

I intend to use a smart home insurance offering in the future.

N8: Future smart home insurance plan.

Given the chance, I plan to use a smart home insurance offering in the near future.

Answer options for each statement: five levels from strongly disagree to strongly agree.

Part O: Intention to adopt smart home

Finally, we are interested to know if you intend to use smart home. Please indicate the level of agreement on the following final statements, with the two smart home examples in mind, and detached from the insurance context.

O1: Intended usage.

I intend to use smart home in the future.

O2: Predicted usage.

I predict I would use smart home in the future.

O3: Opportunistic usage.

If the opportunity presents itself in the near future, I will use smart home.

Answer options for each statement: five levels from strongly disagree to strongly agree.

Appendix B: Pre-test protocol

Phase 1

The questionnaire was tested in four interviews, with participants filling out the questionnaire while reading it aloud and noting incomprehensible parts, followed by a discussion on these issues after completion of the questionnaire. The smart home knowledge of interviewees was rated on a five-level-Likert scale (no knowledge; little knowledge; fair knowledge; good knowledge; very good knowledge).

The interview details are as follows:

Interview date	Interviewee's gender	Interviewee's age (years)	Interviewee's smart home knowledge	Interview duration (minutes)
4 February 2022	female	57	no	25
5 February 2022	male	54	good	15
6 February 2022	female	62	fair	25
6 February 2022	male	61	fair	20

The modifications in the questionnaire resulting from the interviews were the following:

- Changed introductory part of the questionnaire by adding a few simple “icebreaker” questions (e.g., age and gender) to build a flow, in replace of an abstract smart home scenario description at the beginning.
- Questions on social well-being (cf. questions D6.1 to 6.7) extended by the answer option “few times per year” to a five-level-Likert scale.
- Added a question regarding home ownership (question C5).
- Minor wording adjustment in the insurance part N.

Phase 2

In this phase, we ran a test with 50 respondents online via a third-party provider (Bilendi, 17 March 2022). The following fields for feedback were included in the questionnaire (but not included in the final questionnaire):

- Question on the comprehensibility of the smart home examples, measured using a five-level-Likert scale ranging from 1 (not comprehensible) to 5 (comprehensible).
- If comprehensibility of the smart home examples was rated 1 or 2, an open comment box requested information on how comprehensibility can be improved.
- One open comment box at the end of parts L and N requested information on how comprehensibility can be improved regarding the “dimensions of SH adoption” and “risks and costs”, respectively.

The characteristics of the respondents are as follows:

Age class (years)	Gender	Number of responses
45–54	female	8
45–54	male	9
55–64	female	6
55–64	male	9
65–74	female	9
65–74	male	8
75+	male	1

The modifications in the questionnaire resulting from the collected responses were the following:

- Added question regarding safety benefits (questions G2.1 and G2.2) because of the high agreement in all safety related questions.
- Changed title of smart home example 1 (question B1) to “Sensors in the housing” because of feedback that the original title (“Permanently installed sensors”) was associated to elevated installation efforts and would not suit tenants.
- Removed the question “Are facilities and services such as a doctor, pharmacy, or shopping available at your residence (or within 15 minutes driving distance)?” because of a 96% “yes” quota.

Appendix C: Checklist for reporting results of internet e-surveys (CHERRIES)

The following Table 3.15 reports the sample selection and development process of the survey used in this paper according to the CHERRIES guideline (Eysenbach, 2004). We italicize statements that appear in the body of the text and place them in quotation marks.

Table 3.15: CHERRIES checklist.

Item Category	Checklist Item	Reference Location and/or Notes
Design	Describe survey design	<i>“We applied filters based on age (≥ 45 years, aligning with the research focus on AHA), quotas (67:33 ratio for German and French-speaking regions in Switzerland; 50:50 for female and male; 30:30:30:10 for age groups 45–54, 55–64, 65–74, and over 75 years; 10:90 for participants without and with SH knowledge, respectively), and conducted quality checks throughout the survey using control questions.”</i>
	IRB approval	Ethics approval was submitted to the ad hoc commission of the ZHAW School of Management and Law and resulted in a waiver on 13 January 2022.
	Informed consent	The first page, which asked for informed consent in order to participate in the survey, was the following: Welcome to the study on the benefits of smart home systems. This study is conducted by the Institute for Risk and Insurance at the ZHAW School of Management and Law. The survey is strictly confidential and only the ZHAW project team has access to the data collected. All your data will be collected anonymously and cannot be assigned to you personally. If you have any questions, please do not hesitate to contact the university team (project team contact details provided). I agree that my personal data will be processed in accordance with the information provided here. (Yes/No opt-in box provided)
Institutional Review Board (IRB) approval and informed consent process	Data protection	Access to the data set was limited to the authors of this paper. The polling agency also did not have access to the data set. Further, the data were fully anonymized and no data collected could give an inference to an individual person. Data were stored according to best practice guidelines of the Swiss National Science Foundation (SNSF). Access was given only to team members, managed on internal university GitHub, summarized exclusively in aggregated form, and participants could request to have raw data deleted.
Development and pre-testing. Recruitment process and description of the sample having access to the questionnaire	Development and testing	<i>“Prior to its distribution, we conducted a pilot test with individuals who met the eligibility criteria to ensure comprehensibility, usability and technical functionality (see the test protocol in Appendix 3.7)”</i>
	Open survey versus closed survey	The survey was open. Since we worked with a polling agency, most of the respondents were prompted by them to complete our questionnaire.
	Contact mode/ Advertising the survey	<i>“The survey was conducted online in March 2022 using the Unipark software and administered by a professional polling agency responsible for participant recruitment. Participants were provided financial incentives for successful completion and only given the title of the survey when first contacted.”</i>
	Web/E-mail	The survey was created and managed with Unipark. All valid responses were collected via this website.
Survey administration	Context	The survey was not posted on any other website. See Checklist item “Contact mode” and “Advertising the survey” for more information on the polling agency.
	Mandatory/voluntary	Participation was voluntary and participants could opt out at any point of the survey. See Checklist item “Incentives” for more information.

Table 3.15: *Cont.*

Item Category	Checklist Item	Reference Location and/or Notes
	Incentives	The polling agency offered monetary incentives for successful completion. We were given a price per valid participant of EUR 5.70. However, we do not know the effective amount received by the participants. We were not charged for invalid answers (filter criteria and control questions). Therefore, we placed the filter questions at the beginning of the survey and the control questions throughout the questionnaire.
	Time/Date	<i>“The survey was conducted online in March 2022 using the Unipark software and administered by a professional polling agency responsible for participant recruitment.”</i> The exact period was 19–29 March 2022.
	Randomization of items or questionnaires	All items were randomized, except for the questions regarding personal characteristics of the respondent (part A–F of the questionnaire) and the final statements on intention to use a smart home (part O).
	Adaptive questioning	No adaptive questioning or follow-up questions were used.
	Number of Items	<i>“The core of the survey contains 122 questions organized into four categories (personal characteristics, evaluation of prevention benefits, dimensions of SH adoption, risks and costs) and 15 topics labeled from A through O.”</i>
	Number of screens (pages)	A maximum of 15 items were queried on a page in order to keep usability high, resulting in 15 pages/screens.
	Completeness check	There was no completeness check at the end of the survey. However, Unipark made it possible to force an answer on certain questions. We chose to perform this for all items in the main part (parts G to O of the questionnaire).
	Review step	The back button was enabled throughout the questionnaire. No review functionalities were activated.
	Unique site visitor	View rates were defined as those who opened the survey and viewed/loaded the first page of the survey, which was the informed consent page. Visitors were tracked using Unipark’s multiple standard cookies for tracking website visitors.
Response rates	View rate	Not applicable.
	Participation rate	<i>“A total number of 2 553 participants were recruited, with 2 490 agreeing to participate. [...] The final sample consists of 1 515 valid responses.”</i> Details: $N = 2\,553$ participants, 63 disagreed on informed consent page, 409 screened out because of filter questions, 566 screened out in control questions. Total valid participants: $N = 1\,515$.
	Completion rate	$1\,515/2\,490 = 60.8\%$

Table 3.15: *Cont.*

Item Category	Checklist Item	Reference Location and/or Notes
Preventing multiple entries from the same individual	Cookies used	Visitors were tracked using Unipark's multiple standard cookies for tracking website visitors. Duplicate entries were prevented by restricting user access to only one completion.
	IP check	Unipark generates a unique session ID for each respondent on the basis of different cookies and IP tracking. We checked for duplicate entries, which would have been eliminated.
	Log file analysis	None.
	Registration	The survey was publicly accessible and no registration was necessary. However, polling agencies typically work on their own platform where users can track participation in different polls. We do not know the exact mechanism that our polling agency applied.
Analysis	Handling of incomplete questionnaires	Only complete questionnaires were analyzed.
	Questionnaires submitted with an atypical timestamp	The response time averaged 18 min and 57 s, with a median of 16 min and 57 s. Cut-off points for responses that were "too long" or "too short" were not used due to presumed differences in the target groups' technological competence for online questionnaires. Instead, we made use of control questions to test whether the survey was actively and consciously completed.
	Statistical correction	In terms of representativeness, we did not prioritize achieving a defined margin of error. This decision was based on several factors. First, representativeness was not the primary goal; rather, our focus was to conduct exploratory research on SH adoption with a focus on prevention. Second, recruiting the target population, especially those 75 years and older, through an online survey inherently introduces non-representativeness and selection bias. Finally, in our exploratory research, we emphasized the comprehensibility of the questionnaire, appropriate framing in the scenario section, and ensuring respondent engagement usage of control questions. Therefore, we did not adjust for the non-representativeness of the sample, and this fact must be kept in mind when analyzing the results.

Appendix D: Regression analyses

As a supplement to the results of the regression analyses presented in Section 3.4.4, we report here the regression coefficients and significance levels of the logit regression model when applied to the full set of variables related to the SH service and prevention areas (16 constructs, Table 3.16), the AHA characteristics (13 variables, see Table 3.17), and the remaining user characteristics (30 variables, see Table 3.18).

	β -estimate	p -value	Sig.
Intercept	-2.463	<0.001	***
Comfort benefits (G1.1–G1.3, baseline: disagree)			
Neutral	0.135	0.611	
Agree	0.207	0.491	
Safety benefits (G2.1–G2.3, baseline: disagree)			
Neutral	0.192	0.584	
Agree	0.283	0.428	
Health benefits (G3.1–G3.5, baseline: disagree)			
Neutral	0.501	0.020	*
Agree	0.273	0.340	
Fitness benefits (G4.1–G4.4, baseline: disagree)			
Neutral	-0.335	0.083	.
Agree	-0.108	0.721	
Performance expectancy (H1–H6, baseline: disagree)			
Neutral	0.019	0.947	
Agree	0.148	0.655	
Effort expectancy (I1.1–I4.2, baseline: disagree)			
Neutral	-1.009	0.169	
Agree	-0.955	0.184	
Facilitating conditions (J1–J8, baseline: disagree)			
Neutral	1.528	0.013	*
Agree	1.601	0.011	*
Social influences (K1–K4, baseline: disagree)			
Neutral	0.323	0.058	.
Agree	0.495	0.153	
Hedonic motivation (L1–L10, baseline: disagree)			
Neutral	1.359	<0.001	***
Agree	2.376	<0.001	***
Increased dependence (M1.1–M1.2, baseline: disagree)			
Neutral	-0.245	0.168	
Agree	0.067	0.781	
Costs (M2.1–M2.2, baseline: disagree)			
Neutral	-0.706	0.011	*
Agree	-0.987	<0.001	***
Privacy (M3.1–M3.2, baseline: disagree)			
Neutral	0.482	0.056	.
Agree	0.360	0.107	
Other risks (M4.1–M8.2, baseline: disagree)			
Neutral	-0.696	<0.001	***
Agree	-1.059	0.003	**
Insurance costs (N1–N3, baseline: disagree)			
Neutral	-0.092	0.690	
Agree	-0.311	0.221	
Insurance prevention services (N4–N6, baseline: disagree)			
Neutral	-0.204	0.354	
Agree	0.180	0.453	
Interest for insurance offering (N7–N8, baseline: disagree)			
Neutral	0.679	<0.001	***
Agree	1.812	<0.001	***

Note: the significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.16: Results of the logit regression on all constructs (parts G to N of the questionnaire).

	β -estimate	p -value	Sig.
Intercept	-0.857	0.007	**
Mildly strenuous activities (D1.1, baseline: rarely)			
Often	-0.003	0.983	
Really strenuous activities (D1.2, baseline: rarely)			
Often	0.213	0.099	.
Frailty (D2, baseline: no)			
Yes	0.035	0.808	
Satisfaction with life (D3, baseline: dissatisfied)			
Neutral	0.279	0.341	
Satisfied	0.371	0.199	
Depressive symptoms (D4, baseline: no)			
Yes	0.118	0.393	
Loneliness (D5, baseline: rarely)			
Often	0.348	0.063	.
Cultural activity level (D6.1, baseline: rarely)			
Regularly	0.353	0.020	*
Often	0.443	0.098	.
Group sports involvement (D6.2, baseline: rarely)			
Regularly	0.152	0.429	
Often	-0.229	0.146	
Educational courses (D6.3, baseline: rarely)			
Regularly	0.251	0.307	
Often	-0.197	0.412	
Voluntary work (D6.4, baseline: rarely)			
Regularly	-0.014	0.949	
Often	0.030	0.883	
Club activity level (D6.5, baseline: rarely)			
Regularly	-0.005	0.980	
Often	0.237	0.229	
Outing level (D6.6, baseline: rarely)			
Regularly	0.337	0.010	*
Often	0.453	0.013	*
Active grandparent (D6.7, baseline: rarely)			
Regularly	0.054	0.730	
Often	-0.011	0.936	

Note: the significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.17: Results of the logit regression on all active healthy aging variables (part D of the questionnaire).

	β -estimate	p -value	Sig.
Intercept	-2.430	0.002	**
Knowledge level (A1, baseline: poor)			
Mediocre	0.595	<0.001	***
Good	1.278	0.001	***
Convenience application (B1, baseline: dislike)			
Neutral	-0.108	0.726	
Like	1.335	<0.001	***
Health application (B2, baseline: dislike)			
Neutral	0.593	0.004	**
Like	1.246	<0.001	***
Survey language (baseline: DE)			
FR	-0.172	0.314	
Age (A2, baseline: 45–54 years)			
55–64 years	-0.431	0.030	*
65–74 years	-0.481	0.110	
75+ years	-0.703	0.065	.
Gender (A3, baseline: female)			
Male	0.438	0.004	**
Education (C1, baseline: high school)			
Mandatory	-0.033	0.936	
Higher education	-0.123	0.463	
Income sufficiency (C2, baseline: difficult)			
Easy	0.095	0.625	
Expense capacity (C3, baseline: no)			
Yes	-0.139	0.502	
Professional situation (C4, baseline: employed)			
Others	0.120	0.651	
Retired	0.170	0.487	
Home ownership (C5, baseline: rent)			
Ownership	0.413	0.014	*
Marriage / partnership (C6.1, baseline: no)			
Yes	-0.611	0.094	.
Single household (C6.2, baseline: no)			
Yes	-0.476	0.222	
Household with kid(s) (C6.4, baseline: no)			
Yes	-0.198	0.358	
Other households (C6.3/5/6, baseline: no)			
Yes	-0.418	0.373	

Table 3.18: Results of the logit regression on all other personal characteristics variables (parts A to C and E to F of the questionnaire).

	β -estimate	p -value	Sig.
Technology experimenter (E1, baseline: disagree)			
Neutral	0.276	0.209	
Agree	1.216	<0.001	***
Technology pioneer (E2, baseline: disagree)			
Neutral	0.219	0.266	
Agree	0.780	0.001	***
Technology expert (E3, baseline: poor)			
Good	-0.125	0.802	
Excellent	-0.029	0.954	
Mistake avoider (E4, baseline: disagree)			
Neutral	-0.066	0.721	
Agree	0.525	0.009	**
Familiarity preferer (E5, baseline: disagree)			
Neutral	-0.342	0.078	.
Agree	-0.380	0.041	*
Risk-taking level (E6, baseline: not willing)			
Moderately willing	0.024	0.908	
Willing	0.221	0.342	
Suppl. health insurance (F1.1, baseline: Yes)			
No	-0.041	0.819	
Motor vehicle insurance (F1.2, baseline: Yes)			
No	-0.066	0.741	
Travel insurance (F1.3, baseline: Yes)			
No	-0.008	0.959	
Liability insurance (F1.4, baseline: Yes)			
No	0.208	0.468	
Life insurance (F1.5, baseline: Yes)			
No	0.443	0.016	*
Household insurance (F1.6, baseline: Yes)			
No	-0.132	0.691	
Legal expenses insurance (F1.7, baseline: Yes)			
No	0.147	0.355	
Other insurance (F1.8, baseline: Yes)			
No	-0.163	0.613	
Insurance app in use (F2, baseline: Yes)			
No	0.090	0.565	

Note: the significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 3.18: *Cont.*

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Chapter 4

How Customer Expectations on Risk Prevention Shape the Adoption of Smart Home Technology

Smart homes (SH) offer promising opportunities for risk prevention in private households, especially in safety and health. Building on the foundational work of Iten et al. (2024), which outlines the survey development and summarizes descriptive results, we examine the relationship between preventive benefits and adoption intentions. This approach enables a comprehensive analysis of the dynamics between adoption intentions and technology-enabled risk prevention. Our overarching hypothesis is that prevention benefits and comfort considerations positively influence adoption. Using data from a comprehensive survey conducted in Switzerland, we developed a structural equation model to analyze the hypothesized effects while controlling for personality traits. The results reveal significant prevention benefits in safety and health, which are positively related to technology expectations and the intention to adopt SH. Additionally, we confirm the important relationship between comfort and greater adoption intentions. Furthermore, newly included variables such as technology affinity and active aging lifestyle emerge as solid markers of potential SH users, extending the knowledge of user characteristics beyond traditional sociodemographic indicators. The findings fill a gap in research that until now has focused on performance expectations and usability and are relevant for SH device manufacturers and insurers looking to evolve their business models.

Note: This is a joint work with J. Wagner and A. Zeier Röschmann and is under consideration for publication in the special issue on InsurTech: New Technologies and Data in Insurance of the Geneva Papers on Risk and Insurance – Issues and Practice. The authors would like to thank the participants of the 26th International Congress on Insurance: Mathematics and Economics (2023) and the Annual Conference of the Asia-Pacific Risk and Insurance Association (2023) for their feedback on previous versions of this manuscript.

4.1 Introduction

Smart home (SH) technologies are becoming increasingly common due to their potential to improve various aspects of daily life at home (Li et al., 2021). They refer to internet-connected devices and services that enable the transformation of living spaces into remotely managed, digitized, and automated environments (Marikyan et al., 2019). These devices and services are commonly found in the areas of comfort, security, health, and convenience (Sovacool and Furszyfer Del Rio, 2020). Examples include robot vacuum cleaners, smart locks and cameras, smoke alarms, leakage detectors, smart lighting, and thermostats. Zavalova (2023) estimates that the number of smart homes, hence homes equipped with one or more smart home devices, reached 360 million worldwide in 2023, and this number is expected to more than double in the next five years. From a risk management perspective, SH is becoming a valuable tool for preventing and mitigating household risks (Iten et al., 2021). Prevention involves proactive measures to minimize potential risks (Courbage et al., 2013) and Internet of Things (IoT) technologies such as SH use data to gain insights for risk management. Recent research on SH prevention highlights several promising applications, mainly to improve safety and health. For example, SH helps prevent water leaks by monitoring, alerting, and controlling specific water pipes in and around the home (Azam et al., 2017). It also helps reduce injuries at home by preventing falls, ensuring child safety, and detecting unusual movement patterns (Roberts et al., 2019; Torres-Guzman et al., 2023).

Although SH devices are widely used in households and can potentially reduce risks, their main benefits – from a customer’s perspective – are convenience, efficiency, and comfort for daily living (Ayodimeji et al., 2021). Similarly, research has focused mainly on investigating performance expectations and usability (Li et al., 2021). Knowledge of what drives user interest in SH for risk prevention is lacking. Practitioners in the insurance industry describe difficulties in attracting customer interest despite the industry’s expertise in using technology to assess and mitigate risks (Flückiger and Carbone, 2021). Our study builds on prior research, including a recent analysis by Iten et al. (2024), that used the same data set to investigate the associations of individual variables with SH adoption. However, there is a gap in the literature regarding an overarching model from a prevention perspective that comprehensively examines how the preventive capabilities of SH technology influence the adoption intention. Our research contributes to the technology-oriented field of SH research by shedding light on the interplay between technological advances, human perceptions and preferences, and data-driven risk mitigation. Answering this question is also essential for device manufacturers and the insurance industry, which have had limited success in developing prevention-oriented services (Avramakis et al., 2020).

Against this background, we investigate how and to what extent perceived preventive benefits in safety and health and broader considerations of comfort are related to the intention to adopt SH. In addition, our analysis includes various personality traits to characterize potential users. Using data from a comprehensive survey on the dynamics of SH adoption in Switzerland, we build a structural equation model (SEM) to capture the hypothesized effects on the intention to adopt SH, our principal variable. Based on a stepwise selection procedure that has tested 34 regression variables, we extract a set of significant variables related to the personal characteristics of a prospective SH user. To compute the model, we use the method of partial least squares and aim to explain the central relationships within it.

The results indicate that potential users perceive significant preventive benefits in terms of both safety and health. These benefits are positively related to the performance expectations of the technology and the increasing intentions to adopt SH. As suggested by previous research (Li et al., 2021; Nikou, 2019), we confirm that comfort considerations are critical to adoption. Furthermore, specific variables emerge as indicators of SH adopters, including affinity for technology and knowledge, sociodemographics, and active aging lifestyle. Based on technology acceptance research, we gain new insight into the value of prevention for future SH adopters and fill a gap in the so far rather technology-oriented research on SH. The findings also have profound implications for the insurance industry’s approach to the SH technology landscape. We conclude that offerings need to balance both dimensions, convenience and prevention benefits, and would benefit from focusing on user engagement beyond technical capabilities. Additionally, the results indicate that a market strategy targeted at specific segments, such as homeowners or active agers, holds the most promise.

The article is organized as follows. In Section 4.2, we review the literature on SH prevention and adoption, which informs the development of our research hypotheses. We construct the model in Section 4.3 and present the available data. The model results are shown in Section 4.4. In Section 4.5, we discuss our findings and conclude in Section 4.6.

4.2 Theoretical background and research hypotheses

In this section, we provide an overview of the relevant research literature and use it to formulate hypotheses for the subsequent analysis. We begin by analyzing the prevention use cases associated with SH technology. We focus on use cases related to the physical characteristics of a home (property), as prevention benefits associated with wearable technology are beyond the scope of our research. Next, we summarize the drivers of SH adoption and identify the perceived benefits and user characteristics that drive interest in the technology.

4.2.1 Smart home prevention use cases

Prevention is one of many risk management tools. Prevention seeks to influence the frequency or severity of risk by altering its occurrence or consequences (Courbage et al., 2013). IoT technologies, such as SH, promise to improve risk management practices by using data to provide valuable information for risk reduction (Milanović et al., 2020). In the insurance industry, the preventive potential of IoT has been demonstrated primarily through telematics and wearables. Telematics, which focuses on mobility use cases, allows drivers to monitor their driving behavior and receive alerts and recommendations (Ziakopoulos et al., 2022). Wearables focus on health applications by continuously monitoring individual health parameters, promoting a proactive approach to well-being (Soliño-Fernandez et al., 2019). In both cases, suggested behavioral changes are incentivized to promote safer practices, reduce claim costs, and align insurers and policyholder interests (Ramcharan, 2021).

SH also promises opportunities for risk prevention. Flückiger and Carbone (2021) note that the capabilities of real-time safety enhancement by technology have led insurers to speculate about the potential to reduce exposure to household risk and vulnerability to risks typically covered by insurance policies. Several promising use cases have emerged internationally, particularly

among insurers in the United States. An example is Hippo’s home insurance offering, which includes smart devices to mitigate water damage, fire, and unauthorized access. An example of a European insurance offering is Luko in France. The company started in 2018 with a strong focus on SH prevention but gradually reduced its IoT activities. Finally, in the summer of 2023, the company sold its entire policy portfolio. Enzo, a German InsurTech company, has recently adopted the prevention premise of SH to reduce water leaks in homes. A comprehensive literature review by Iten et al. (2021) details the household risks that SH technology can effectively address. The authors identified several emerging threats, including privacy and cybersecurity risks, performance and dependency risks, and everyday household risks related to theft, fire, water, and health.

Table 4.1 summarizes the prevention use cases identified in the literature. We associate the risks and cases of SH use with existing SH products. The results are organized according to the specific risks they address in safety, health, energy management, and cybersecurity.

In the *safety* domain, SH prevention use cases focus primarily on common household risks (Sevilano, 2018). For example, SH contributes to preventing unauthorized access risks by simulating presence during absence, efficiently managing door access, and detecting intrusions. These use cases are realized through integrating various SH products, including door locks, video doorbells, motion sensors, and lighting systems (Sovacool and Furszyfer Del Rio, 2020). Fire prevention is another prominent area, which involves the detection of smoke and carbon monoxide, automatic shutdown mechanisms, and interactive assistance with escape routes. Products such as smoke detectors, water sprinklers, and smart kitchen appliances are instrumental in these efforts (Saeed et al., 2018). Safety-related use cases also extend to the prevention of water leakage and the mitigation of natural hazards. These include monitoring, notification, and control capabilities for specific parameters affecting the home and its surroundings (Azam et al., 2017).

Health-related SH prevention use cases are difficult to distinguish from other IoT applications in daily life (Turjamaa et al., 2019) and often involve wearables and home applications. Most of the research comes from studies of specific diseases or demographics (Carnemolla and Bridge, 2020). These studies often focus on older adults or people in care settings. An often explored health-focused application is injury prevention, including use cases to prevent falls, ensure child safety, and detect unusual movement patterns. Motion sensors, cameras, and medical alert systems are critical in these efforts (Carnemolla and Bridge, 2020). In addition, health-related use cases extend to preventing frailty (VandeWeerd et al., 2020) and helping with cognitive impairment (Wrede et al., 2022).

Energy management is a growing area of research, with SH recognized as a critical lever in the contribution of households to a solution to climate-related challenges (Acoca et al., 2018). Numerous use cases in this area aim to reduce inefficient consumption habits. Smart thermostats, plugs, water valves, and integrated heating and cooling systems enable monitoring and optimizing energy and water use, automating routines of household appliances, and localized production and consumption of solar energy (Amin et al., 2021).

Cybersecurity and privacy concerns represent significant emerging risks related to adopting SH technology (Klobas et al., 2019). Preventive measures are mainly derived from research in information security, focusing on failure and intrusion detection systems. In addition to these

Risks and SH use cases	SH products	References
Safety domain		
<i>Unauthorized access</i>		
<ul style="list-style-type: none"> – Simulate presence – Door entry management – Intrusion detection – Activation of panic scenarios – Windows monitoring 	Smart door lock, video doorbell, motion sensor lock, alarm system, smart light, window controller, camera	Acoca et al. (2018); AXA (2019); Blythe and Johnson (2019); Feuerstein and Karmann (2017); Kivimäki et al. (2020); Sovacool and Furszyfer Del Rio (2020); Sevillano (2018); Tural et al. (2021)
<i>Fire</i>		
<ul style="list-style-type: none"> – Smoke and CO₂ detection – Shutdown and sprinkler systems – Escape plan assistance 	Smoke alarm, water sprinkler system, interactive fire escape plan, intelligent kitchen appliances	Acoca et al. (2018); Gielen et al. (2018); Hsu et al. (2019); Karemaker et al. (2021); Saeed et al. (2018); Salhi et al. (2019); Sevillano (2018); Sovacool and Furszyfer Del Rio (2020); Tural et al. (2021)
<i>Natural hazard</i>		
<ul style="list-style-type: none"> – Weather monitoring – Earthquake detection – Wildfire warnings 	Weather station, seismic sensor, wildfire alert system, window controller	Azam et al. (2017); Feuerstein and Karmann (2017); Sevillano (2018)
<i>Water damage</i>		
<ul style="list-style-type: none"> – Leaks and flood detection – Humidity control – Freezing and bursts prevention – Emergency shut off 	Leak detection sensor, flood sensor, humidity control system, smart water valve	Azam et al. (2017); Davis (2020); Feuerstein and Karmann (2017); Sevillano (2018)
Health domain		
<i>Cognitive impairment</i>		
<ul style="list-style-type: none"> – Dementia monitoring – Voice-control assistance – Cognitive support 	Activity sensor, voice-activated assistant, digital assistant	Brims and Oliver (2019); Carnemolla and Bridge (2020); Liu et al. (2016); Oyeleke et al. (2020); Saragih et al. (2023); Wrede et al. (2022)
<i>Frailty</i>		
<ul style="list-style-type: none"> – Family member care – Promotion of exercise routines – Nutrition patterns monitoring 	Activity sensor, smart camera, exercise machine, intelligent kitchen appliances	Carnemolla and Bridge (2020); Crane et al. (2022); Gómez-Portes et al. (2021); Hsu et al. (2019); Kracht and Staiano (2022); Liu et al. (2016); Murri et al. (2021); Romero et al. (2018); Sovacool and Furszyfer Del Rio (2020); VandeWeerd et al. (2020); Welch et al. (2021)
<i>Injuries</i>		
<ul style="list-style-type: none"> – Falls and injuries prevention – Ensuring child safety – Unusual movements detection 	Medical alert system, child-proofing sensor, motion sensors, camera	Abbassinia et al. (2019); Ambrens et al. (2023); Ma et al. (2022); McKenzie et al. (2021); Miranda-Duro et al. (2021); Nose et al. (2019); Pech et al. (2021); Roberts et al. (2019); Torres-Guzman et al. (2023); Wright et al. (2021)
Energy management domain		
<i>Waste of resources</i>		
<ul style="list-style-type: none"> – Energy usage optimization – Automation of appliances – Water resources management – Protection against power surges – Solar energy utilization – Electric vehicles charging 	Smart thermostat, smart plug, smart water valve, smart sprinkler controller, solar panel, electric car charger, intelligent heating/ cooling system	Amin et al. (2021); Fernández-Caramés (2015); Jones-Garcia et al. (2022); Psomas et al. (2017); Sovacool and Furszyfer Del Rio (2020)
Cybersecurity domain		
<i>Cybersecurity and privacy</i>		
<ul style="list-style-type: none"> – Technical treatment – Raising awareness – Knowledge dissemination – User empowerment 	Not available	Al-Begain et al. (2022); Ali and Hong (2018); Buil-Gil et al. (2023); Hammi et al. (2022); Jacobsson et al. (2016); Klobas et al. (2019); Pecorella et al. (2018)

Table 4.1: Review of selected risks and SH use cases addressed by SH products in the safety, health, energy management, and cybersecurity domains.

technical studies, other work focuses on the knowledge that SH users need to proactively reduce their exposure to cyber risks (Jacobsson et al., 2016).

4.2.2 Determinants of smart home adoption

The literature on technology adoption is critical to understanding the users' perspectives on SH. This body of research provides information on the factors that shape an individual's decision to adopt and use SH technology (Hubert et al., 2019). Technology acceptance models have evolved based on the seminal work of Davis (1989). For example, an overview of the technology acceptance model and the unified theory of acceptance and use of technology model applied in the SH context can be found in Iten et al. (2024) and Marikyan et al. (2019). Empirical evidence focuses on three issues: SH service areas and their benefits to users; the factors related to the adoption of SH, with particular emphasis on the concept of general usefulness or performance expectation of the technology; and the study of specific personality traits that characterize potential SH users.

Service areas and benefits The main SH service areas include comfort, energy management, health, and safety (Li et al., 2021). In the area of comfort, SH services aim to improve the lives of residents by simplifying daily tasks and giving them greater control over household appliances, thus providing additional comfort (Chan et al., 2012). SH energy services focus on reducing energy consumption through continuous monitoring and automation, significantly contributing to sustainability efforts by optimizing energy use (Reinisch et al., 2011). Health services address individual health and environmental information needs, often focusing on older adults or individuals with disabilities, to promote healthier and more independent living (Tural et al., 2021). Safety services enable residents to strengthen home safety, prevent accidents, and minimize financial losses (Blythe and Johnson, 2019). Moreover, these essential service areas provide the expected benefits of SH and have a critical impact on the take-up of the technology by the typical household (Marikyan et al., 2019).

Key drivers for adoption Among the main drivers of the adoption of SH, performance expectation or perceived usefulness of SH plays a pivotal role in shaping individuals' intentions to adopt (Tural et al., 2021). As individuals assess the benefits associated with SH, their assessment of the usefulness of the technology becomes a critical factor in their decision-making process (Baudier et al., 2020). In studies of SH adoption, researchers often contextualize SH's utility in increasing perceived productivity, efficiency, and overall effectiveness in performing daily household tasks (Nikou, 2019). As such, the focus is typically on convenience, particularly automation of everyday household tasks. According to Li et al. (2021), comfort considerations are generally emphasized as the primary driver of SH adoption. Few studies have examined preferences for benefits in other service areas; for example, Chang and Nam (2021). These authors compared the relative importance of all four service areas in driving adoption intentions. The results highlighted the importance of comfort as the main driver, followed by safety considerations. More recent work has examined additional factors such as enabling conditions and social influences (Sequeiros et al., 2021; Alaiad and Zhou, 2014), fun and enjoyment (Nikou, 2019; Große-Kreul, 2022), perceived value of investing in technology (Tural et al., 2021), and barriers and risks (Loi et al., 2017).

Prospective user’s characteristics Knowing the personal characteristics of a potential SH user can be helpful because it can indicate which individuals are more likely to recognize the benefits of SH (Jansen et al., 2021). However, the results in this area are mixed and sometimes contradictory. Younger adults tend to show higher adoption intentions than older adults (Wang et al., 2020). However, studies by Shin et al. (2018) and Klobas et al. (2019) have observed higher adoption rates among older adults, particularly in SH health settings, where they are more willing to share personal data. The influence of gender on SH dynamics remains inconclusive. Sovacool et al. (2021) suggest that the effect of gender is related to the underlying promise of SH, observing significant differences between a promise focused on entertainment and reduced housework. Higher income and education levels positively correlate with SH interest (Klobas et al., 2019), although Chang and Nam (2021) suggest that this effect may be related to the cost associated with technology. The essential characteristics of SH users are experience and affinity for technology, previous experience with SH (Shank et al., 2021), awareness and knowledge of SH technologies (Wilson et al., 2017), ownership of other technologies (De Boer et al., 2019), and ownership and expertise of a smartphone (Tural et al., 2021). All are associated with higher levels of adoption of SH. Furthermore, marital status (Arthanat et al., 2019), homeownership (Arthanat et al., 2019), and household size (Tural et al., 2021) were found to be related to SH adoption.

4.2.3 Hypotheses development

To guide our subsequent analysis, we develop hypotheses that synthesize information from SH prevention use cases and factors influencing technology adoption. These hypotheses consider performance expectations, personal characteristics, and comfort, safety, and health benefits. Our approach aims to provide a comprehensive overview of the factors that influence the adoption of SH technology in the context of its promise for risk prevention in Switzerland.

Prevention use cases studied in industry and academia highlight the importance of addressing health and safety considerations. These use cases focus on safety-related applications, such as preventing fires and water damage, and health-related applications, such as preventing injuries and helping people with cognitive impairments. Given the particularly central role of safety and health research in SH prevention, we propose the following hypotheses.

- (H1) *Safety and health prevention benefits and performance expectations correlate positively.*
- (H2) *Safety and health prevention benefits and SH adoption intention correlate positively.*

Research on SH adoption has mainly focused on the comfort aspect of technology and its influence on shaping performance expectations and SH adoption intentions. By validating the role of comfort in the context of the prevention aspects explored above, we further strengthen its validity and importance. Therefore, we propose to test the following hypotheses:

- (H3) *Comfort benefits and performance expectations correlate positively.*
- (H4) *Comfort benefits and SH adoption intention correlate positively.*

Performance expectation is one of the main drivers of adopting SH technology identified in the literature. This facet highlights how people evaluate the practical usefulness and benefits they expect from incorporating SH into their homes. As a critical component of the adoption decision process, we propose the following hypothesis:

(H5) Performance expectation and SH adoption intention correlate positively.

Furthermore, the literature on SH adoption presents inconclusive results on personality traits contributing to increased interest in SH. Given these unknown relevant personal characteristics of a potential SH user, we hypothesize that:

(H6) Personal characteristics and SH adoption intention may correlate positively or negatively.

4.3 Model framework and survey data

This section provides a comprehensive overview of the model and data used to investigate the research question and test the hypotheses presented. Our approach focuses on three main elements: the SEM, whose visual representation also illustrates the hypothesized relationships; the methodology used to compute the model, which outlines the techniques used to estimate our model; and the data set selected to facilitate our analysis.

4.3.1 Structural equation model

We chose partial least squares SEM (PLS-SEM) as our primary methodology to investigate the hypothesized relationship. SEM studies are highly regarded in the social sciences for their practicality and effectiveness (Hair et al., 2012; Kalouguina and Wagner, 2020). A significant advantage of PLS-SEM is its ability to handle different types of measures efficiently. This is particularly valuable when studying complex concepts that are not directly observable, often referred to as latent “constructs,” such as the benefits of SH technology, which are influenced by numerous specific factors and beliefs. In PLS-SEM, constructs can act as exogenous drivers or be considered endogenous by other variables. To fully reflect the nature of a construct, we use manifest variables called measures or “indicators.” In general, several indicators measure constructs representing a particular aspect of a construct. However, for simplicity, we also use “single-items” to refer to constructs measured directly by a single observable variable, eliminating the need for multiple indicators in the modeling process.

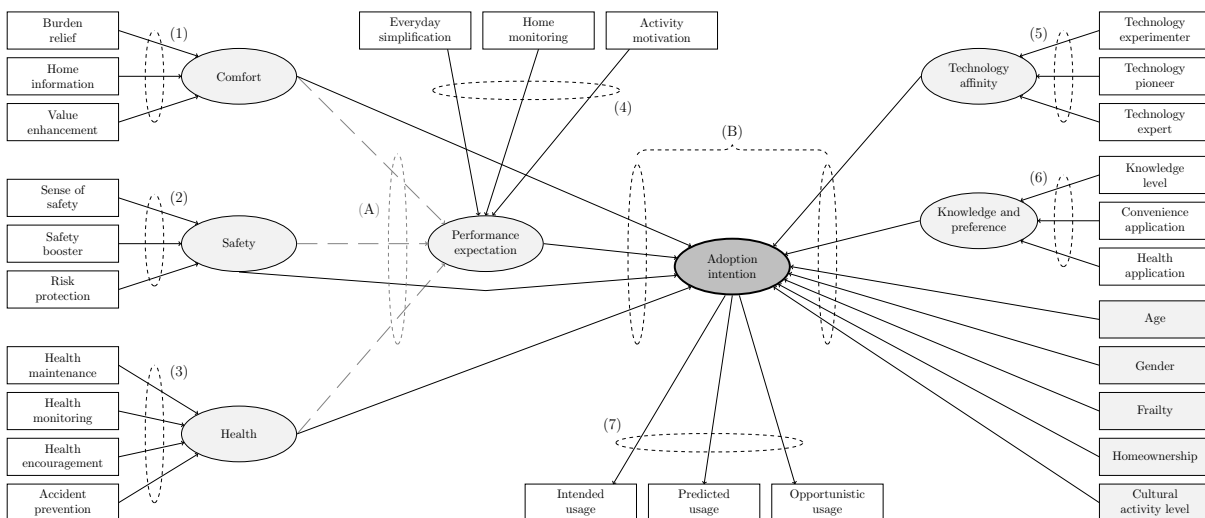


Figure 4.1: Illustration of the complete structural model, including all measures.

Figure 4.1 shows the complete model we are considering. On the graph, the numbers from (1)

to (7) denote the measurement models relating the latent constructs to their indicators, and the letters (A) and (B) represent the structural models (Hair et al., 2021). The complete set of variables, including the labels, their type, a description, the values taken, and the reference to the source in the original questionnaire (see Iten et al., 2024, Appendix A) is reported in Table 4.2.

Variable	Label	Type	Description	Values	Source
<i>COM</i>	<i>Comfort</i>	<i>Exo</i>	<i>Broad comfort benefits</i>	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	
<i>BRE</i>	Burden relief	Ind	Reduce burden of household activities	"	G1.1
<i>HIO</i>	Home information	Ind	Provide information and control options	"	G1.2
<i>VEN</i>	Value enhancement	Ind	Maintain or increase property value	"	G1.3
<i>SAF</i>	<i>Safety</i>	<i>Exo</i>	<i>Prevention benefits related to safety</i>	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	
<i>SOS</i>	Sense of safety	Ind	Make feel more safely	"	G2.1
<i>SBO</i>	Safety booster	Ind	Increase home safety	"	G2.2
<i>RPR</i>	Risk protection	Ind	Protect against risks at home	"	G2.3
<i>HEA</i>	<i>Health</i>	<i>Exo</i>	<i>Prevention benefits related to health</i>	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	
<i>HMA</i>	Health maintenance	Ind	Take care of oneself and avoid doctor visit	"	G3.1
<i>HEM</i>	Health monitoring	Ind	Monitor easily health metrics	"	G3.2
<i>HEN</i>	Health encouragement	Ind	Motivate to behave healthier	"	G3.3
<i>APR</i>	Accident prevention	Ind	Help to prevent accidents and health risks	"	G3.4
<i>PEX</i>	<i>Performance expectation</i>	<i>Endo</i>	<i>Usefulness unrelated to service areas</i>	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	
<i>ESI</i>	Everyday simplification	Ind	Simplify everyday household activities	"	H1
<i>HOM</i>	Home monitoring	Ind	Monitor effectively state or progress of home	"	H2
<i>AMO</i>	Activity motivation	Ind	Motivate to do activities that don't like to do	"	H3
<i>TAF</i>	<i>Technology affinity</i>	<i>Exo</i>	<i>Familiarity with technology usage in general</i>	Five levels from <i>low</i> to <i>high</i>	
<i>TEX</i>	Technology experimenter	Ind	Pleasure in trying new technologies	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	E1
<i>TPI</i>	Technology pioneer	Ind	First to try new technologies	"	E2
<i>TXT</i>	Technology expert	Ind	Skills in using the smartphone or tablet	Five levels from <i>poor</i> to <i>excellent</i>	E3
<i>KAP</i>	<i>Knowledge and preference</i>	<i>Exo</i>	<i>Prior knowledge and preference for a service area</i>	Five levels from <i>low</i> to <i>high</i>	
<i>KLE</i>	Knowledge level	Ind	Level of experience in SH	Five levels from <i>no</i> to <i>very good knowledge</i>	A1
<i>CAP</i>	Convenience application	Ind	Preferences for sensors serving convenience	Five levels from <i>dislike</i> to <i>like</i>	B1
<i>HAP</i>	Health application	Ind	Preferences for mobile health device	"	B2
<i>AGE</i>	Age	Single	Age in years	45–90 years	A2
<i>GEN</i>	Gender	Single	Gender of the respondent	Female, male	A2
<i>FRA</i>	Frailty	Single	Frailty in certain everyday activities	No, yes	D2
<i>HOW</i>	Homeownership	Single	Main residence ownership	Renter, owner	C5
<i>CAL</i>	Cultural activity level	Single	Participation in cultural activities	Hardly ever, few times a year, 1-2x month, 1x week, >1x week	D6.1
<i>AIN</i>	<i>Adoption intention</i>	<i>Endo*</i>	<i>Intention to adopt SH</i>	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>	
<i>IUS</i>	Intended usage	Ind	Intention to use technology in the future	"	O1
<i>PUS</i>	Predicted usage	Ind	Prediction to use technology in the future	"	O2
<i>OUS</i>	Opportunistic usage	Ind	Intention to use technology when opportunity arises	"	O3

Note: The column "Type" uses the abbreviations "Exo" for exogenous variables, "Endo" for endogenous variables, "Ind" for indicator variables, and "Single" for single-item variables. The references in column "Source" refer to the original survey data defined in Iten et al. (2023). *Adoption intention *AIN* is the principle variable of interest.

Table 4.2: Overview of the variables used in the model.

4.3.2 Available survey data

Our study uses data from a recent survey on SH adoption in Switzerland (Iten et al., 2023). The survey aimed to assess established determinants of SH adoption and potentially relevant features and user characteristics from a risk prevention perspective. A professional polling agency conducted the survey in 2022, targeting individuals aged 45 years and older. Participation was incentivized for successful completion. Additional sample quotas and control questions were defined based on the respondents' age, gender, language, and SH knowledge level. Originally, a total of 2553 responses were received, resulting in 1515 final observations after quotas and control. Iten et al. (2024, Sect. 3.1) provide a detailed description of the survey's development, structure and operationalization. Based on the methodology laid out in the benchmark articles by Becker et al. (2022); Hair et al. (2021); Sanmukhiya (2020) in the field of PLS-SEM, we examined the data set in five key areas to assess its quality. Although this procedure did not reveal any problems with missing data, data distribution, and common-method bias, we identi-

fied two suspicious responses and 11 outliers that we removed from the sample (see Table 4.7 in the Appendix). Therefore, the final sample used in this study consists of 1 502 responses. For our analysis, we extract the relevant variables, comprising indicators on SH adoption intention (three variables) and performance expectation (three variables), ten variables on the benefits of SH (excluding four variables related to fitness), as well as a comprehensive set of variables related to personal characteristics (34 variables).

<i>Distribution of the survey respondents (in %)</i>					
<i>Age (AGE)</i>		<i>Gender (GEN)</i>		<i>Knowledge level (KLE)</i>	
45–54 years	30.0	Female	50.2	Poor	59.9
55–64 years	30.0	Male	49.8	Mediocre	32.2
65–74 years	30.3			Good	7.9
75+ years	9.7				
<i>Distribution of the survey answers in the indicator variables for adoption intention (in %)</i>					
<i>Intended usage (IUS)</i>		<i>Predicted usage (PUS)</i>		<i>Opportunistic usage (OUS)</i>	
Disagree	35.6	Disagree	33.8	Disagree	31.7
Neutral	30.8	Neutral	26.3	Neutral	20.5
Agree	33.6	Agree	39.9	Agree	47.8

Table 4.3: Survey sample characteristics ($N = 1\,502$).

In Table 4.3, we present the distribution of the survey respondents according to age, gender, and level of knowledge of SH, as well as statistics on the responses related to the principal variable of interest, the adoption intention. In terms of representativeness, the distribution is balanced by gender, but there is a slight overrepresentation of the 65–74 age group at the expense of those aged 75 and older. The three indicators of adoption intention show that slightly more people expressed an intention to adopt SH than those who did not. However, most of the respondents reported low levels of knowledge of SH. Both observations are consistent with the patterns found in recent studies on SH adoption (Große-Kreul, 2022). Iten et al. (2024) provide descriptive statistics for all variables in the dataset for the intention to adopt SH.

4.3.3 Methodology, measurements, and model specification

Methodology PLS-SEM uses a two-stage modeling approach that involves first estimating the measurement models, which describe the relationships between the observed indicators and the latent constructs (see Equations 1 to 7 below and Figure 4.1), and then estimating the structural models, which describe the relationships between the constructs and the single items considered (models A and B). In the first step, the indicator scores for a construct are combined to form a composite score using a linear weighting process (Sarstedt et al., 2014).¹ In this process, Likert-scale responses are treated as ordinal variables and coded numerically using a scale ranging from 1 to 5. PLS-SEM can effectively handle ordinal variables, even when the numerical values do not represent equidistant intervals, as it focuses on the covariance struc-

¹This contrasts with the standard factor-based SEM (CB-SEM), where the constructs are treated as common factors that explain the covariance between their associated indicators (Dash and Paul, 2021). This approach is consistent with the so-called “reflective” measurement philosophy, where all indicators and their covariance are considered manifestations of the underlying construct. However, in “formative” measurements, the construct is formed by its underlying indicators rather than representing a construct. The composite-based approach of PLS-SEM is the preferred method for models involving such measurements (Hwang et al., 2020). It relaxes the strong assumptions of CB-SEM, where all relationships between sets of indicators are explained by a common factor (Rigdon, 2014).

ture rather than a specific distributional assumption (Hair et al., 2021). In the second step, PLS-SEM estimates the path coefficients, i.e., the hypothesized relationships. Using ordinary least squares (OLS) regression and the standardized scores from the first step, the algorithm regresses the exogenous constructs on the endogenous constructs. The goal is to maximize the explained variance of the endogenous constructs, especially our principal variable, the intention to adopt SH. We measure the explained variance by the models' R -squared values. PLS-SEM is the preferred method for developing theory and explaining variance (Becker et al., 2022).

In the following, we describe two types of measurements, formative and reflective, which provide the theoretical basis for computing the first step of the PLS-SEM. We then present the regression model used to estimate the path coefficients in the second step. For this, we also consider a stepwise variable selection procedure to select the final set of variables related to personal characteristics.

Formative measurements A formative construct is defined by specific individual aspects, each captured by an indicator. The construct is formed by its indicators, each representing a different aspect of the latent construct (Gudergan et al., 2008). The six formative constructs used in our model are derived from the literature reviewed in Sect 4.2. They include comfort (COM), safety (SAF), health (HEA), performance expectation (PEX), technology affinity (TAF), and knowledge and preference (KAP). The constructs have been validated in various technology adoption contexts, providing a robust theoretical foundation. In addition, they have been validated on the data (Iten et al., 2024, Table 7). The following equations define the composite scores of the six formative constructs that appear in our model.

$$COM_i = \omega_{BRE} \cdot BRE_i + \omega_{HIO} \cdot HIO_i + \omega_{VEN} \cdot VEN_i, \quad (1)$$

$$SAF_i = \omega_{SOS} \cdot SOS_i + \omega_{SBO} \cdot SBO_i + \omega_{RPR} \cdot RPR_i, \quad (2)$$

$$HEA_i = \omega_{HMA} \cdot HMA_i + \omega_{HEM} \cdot HEM_i + \omega_{HEN} \cdot HEN_i + \omega_{APR} \cdot APR_i, \quad (3)$$

$$PEX_i = \omega_{ESI} \cdot ESI_i + \omega_{HOM} \cdot HOM_i + \omega_{AMO} \cdot AMO_i, \quad (4)$$

$$TAF_i = \omega_{TEX} \cdot TEX_i + \omega_{TPI} \cdot TPI_i + \omega_{TXT} \cdot TXT_i, \quad (5)$$

$$KAP_i = \omega_{KLE} \cdot KLE_i + \omega_{CAP} \cdot CAP_i + \omega_{HAP} \cdot HAP_i. \quad (6)$$

To estimate the indicator weights ω , a multiple regression is employed, whereby the construct is treated as the dependent variable and its indicators as independent variables (Hair et al., 2021). The standardized regression weights thus obtained represent the relative importance of each indicator in contributing to the overall construct. Minimizing the deviation between observed indicators and predicted construct scores, ω quantifies the strength and the direction of the relationship between each indicator and the construct. This process allows for a comprehensive assessment of the contribution of each indicator to the formation of the construct, thereby providing insight into its composition based on observed data.

Reflective measurements A reflective construct assumes that the construct causes all indicators. Thus, the indicators are highly correlated and interchangeable in meaning (Gudergan et al., 2008). Our model contains only one reflective construct, the intention to adopt SH (AIN), which is measured by three indicators: intended usage (IUS), predicted usage (PUS), and opportunistic usage (OUS). The variables measure the intention to adopt SH technology. By utilizing three variables, which were asked and formulated at different points in the survey,

we can ensure higher reliability and validity. The variables and the resulting construct are drawn from previous studies on SH adoption (see, e.g., Baudier et al., 2020; Große-Kreul, 2022; Sequeiros et al., 2021). A set of three equations (see Equation 7) reflects the relationship from the construct to each of the indicators:

$$\begin{aligned}
 IUS_i &= \iota_{IUS} \cdot AIN_i + \varepsilon_{IUS,i}, \\
 PUS_i &= \iota_{PUS} \cdot AIN_i + \varepsilon_{PUS,i}, \\
 OUS_i &= \iota_{OUS} \cdot AIN_i + \varepsilon_{OUS,i}.
 \end{aligned} \tag{7}$$

The indicator loadings ι are estimated through bivariate regressions, considering the unexplained variance (Hair et al., 2021). As a result, we obtain correlation weights between the construct and each of its indicators, which represent how well each indicator reflects the underlying construct. We assume that the error terms ε are uncorrelated with each other and the construct, resulting in a mean value of zero.

Structural models In the second step of PLS-SEM, we use OLS regression to estimate the structural models. The hypothesized model comprises two endogenous constructs, performance expectation (PEX) and adoption intention (AIN), which results in the regression equations (A) and (B).

Equation (A) shows the regression model depicting the relationship between performance expectation and the three exogenous constructs perceived comfort (COM), safety (SAF), and health (HEA) benefits:

$$\overline{PEX}_i = \lambda_0 + \lambda_{COM} \cdot COM_i + \lambda_{SAF} \cdot SAF_i + \lambda_{HEA} \cdot HEA_i + \varepsilon_{PEX,i} \tag{A}$$

where we use the notation \overline{PEX}_i to distinguish it from the composite score PEX_i defined in Equation (4). The λ s are the estimated intercept and coefficients, respectively, and ε_{PEX} is the error term. Since the construct scores that result from the first step represent standardized values, PLS-SEM also applies data standardization in the regression. As a result, the intercept is zero, and the coefficients range between -1 and $+1$. Furthermore, a coefficient of $+1$ indicates a strong positive correlation, while negative values indicate a negative correlation. Values close to zero are associated with weaker relationships (Hair et al., 2021).

Equation (B) describes the regression model linking the principal variable of interest, the adoption intention (AIN), with its respective variables. The model we present in Figure 4.1 consists of two parts. The variables pointing from the left of the graph to the AIN variable represent different aspects of SH benefits, including comfort (COM), safety (SAF), health (HEA), and performance expectation (PEX). They make what we call the “base model.”

The variables pointing from the right of the graph relate to the personal characteristics of a potential SH user. The final set of variables used in the model (see Figure 4.1) results from a stepwise selection procedure used to understand which personality traits described by the 34 variables available in the survey data (see Section 4.3.2) contribute significantly to explain the adoption of SH. Starting from the “base model”, we incrementally added explanatory variables to find the model that best describes the intention to adopt. A variable was only kept if the resulting regression model yielded an improved R -squared value, a lower value of the Bayesian information criterion (BIC), significant regression coefficients (p -value below 0.05), and no multicollinearity problems (variance inflation factor, VIF, value below 3.3); see, for ex-

ample, Arthanat et al. (2019). Details of the intermediate regression models verified during the selection procedure are provided in Table 4.8 in the Appendix. The final regression model includes the constructs of technology affinity (TAF) and knowledge and preference (KAP), as well as age (AGE), gender (GEN), frailty (FRA), homeownership (HOW) and cultural activity level (CAL).

The model for the intention to adopt SH writes out as follows:

$$\begin{aligned} AIN_i = & \beta_0 + \beta_{COM} \cdot COM_i + \beta_{SAF} \cdot SAF_i + \beta_{HEA} \cdot HEA_i + \beta_{PEX} \cdot PEX_i \\ & + \beta_{TAF} \cdot TAF_i + \beta_{KAP} \cdot KAP_i + \beta_{AGE} \cdot AGE_i + \beta_{GEN} \cdot GEN_i \\ & + \beta_{HOW} \cdot HOW_i + \beta_{FRA} \cdot FRA_i + \beta_{CAL} \cdot CAL_i + \varepsilon_{AIN,i}. \end{aligned} \quad (B)$$

From the standardization applied in step one, the intercept β_0 is zero; the other β s are the estimated regression coefficients, and ε_{AIN} denotes the error term.

4.4 Results

In this section, we present the results of the PLS-SEM calibration using SmartPLS 4 software. First, we validate the measurement models defined using Equations (1) to (7). Then, we provide the results of the regression models for performance expectation (model A) and adoption intention (model B). When presenting the results, we discuss key metrics on the performance of the models (Danks et al., 2020).

4.4.1 Validation of the measurement models

Formative measurements To evaluate the validity of each formative construct, we discuss a set of metrics as suggested by Becker et al. (2022) and Hair et al. (2021). First, *content validity* refers to the degree to which the selected indicators accurately and comprehensively capture the content of a construct. The goal is to ensure that the indicators effectively represent the depth of a construct. The survey was based on strong theoretical and empirical foundations following a literature review, exploratory interviews, and pre-tests to achieve this (see the procedure described in Iten et al., 2024, Appendix B). Second, *indicator collinearity* refers to a potential correlation between indicators, which can negatively impact the standard error of the indicator weights and complicate the estimation of each indicator’s unique contribution. We use the VIF metric to assess the collinearity of indicators and find that all indicators’ VIF values are below the cautious threshold of 3.3. We observe that the health maintenance (HMA), safety booster (SBO), and health monitoring (HEM) variables exhibit the highest VIF values of 2.832, 2.795, and 2.625, respectively. Third, we assess the *significance and relevance* of the indicators. The values of the indicators’ weights and associated significance levels provide information on the relative importance of each indicator in the corresponding construct. We report these levels in Table 4.4. We observe that through all constructs, the coefficients of the indicators yield high significance levels, with a single exception that the indicator related to technology expertise (ω_{TXT}) is not significant in the technology affinity construct (Equation 5). However, we retain it as an indicator for content validity reasons. The literature on personal characteristics of SH users suggests that measuring the affinity of technology should include several aspects related to technology, such as ownership, expertise, and familiarity (see Section 4.2.2). With the above, we conclude that all constructs are valid.

Equation	Construct	Indicator		Coefficient	Sig.
<i>Formative constructs</i>					
(1)	Comfort	Burden relief	ω_{BRE}	0.261	***
		Home information	ω_{HIO}	0.700	***
		Value enhancement	ω_{VEN}	0.243	***
(2)	Safety	Sense of safety	ω_{SOS}	0.552	***
		Safety booster	ω_{SBO}	0.169	**
		Risk protection	ω_{RPR}	0.419	***
(3)	Health	Health maintenance	ω_{HMA}	0.191	**
		Health monitoring	ω_{HEM}	0.496	***
		Health encouragement	ω_{HEN}	0.284	***
		Accident prevention	ω_{APR}	0.178	***
(4)	Performance expectancy	Everyday simplification	ω_{ESI}	0.463	***
		Home monitoring	ω_{HOM}	0.378	***
		Activity motivation	ω_{AMO}	0.310	***
(5)	Technology affinity	Technology experimenter	ω_{TEX}	0.642	***
		Technology pioneer	ω_{TPI}	0.407	***
		Technology expert	ω_{TXT}	0.058	
(6)	Knowledge and preference	Knowledge level	ω_{KLE}	0.453	***
		Convenience application	ω_{CAP}	0.524	***
		Health application	ω_{HAP}	0.387	***
				Loading	Cronbach's α
<i>Reflective construct</i>					
(7)	Adoption intention	Intended usage	ι_{IUS}	0.965	0.960
		Predicted usage	ι_{PUS}	0.970	
		Opportunistic usage	ι_{OUS}	0.952	

Note: The significance values in column ‘‘Sig.’’ are coded as follows: * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 4.4: Validation of the formative and reflective constructs.

Reflective measurements We evaluate reflective measurements for their reliability and validity using metrics related to indicator reliability, internal consistency, convergence validity, and discriminant validity (Gudergan et al., 2008; Hair et al., 2021). The reflective measurement adoption intention (*AIN*) meets the commonly accepted thresholds for the metrics and is thus reliable and valid for our research context. First, *indicator reliability* is demonstrated by the squared values of the loadings, which represent the strength and direction of the relationships between the latent construct and its observed indicators (see Table 4.4). We find the following squared values for the three indicators: intended usage (*IUS*) 0.931, predicted usage (*PUS*) 0.941, and opportunistic usage (*OUS*) 0.906. All values exceed the commonly accepted threshold of 0.708 (corresponding to the construct explaining at least 50% of the indicator’s variance). Second, *internal consistency* assesses the ability of indicators to measure the same underlying construct. It is typically evaluated using Cronbach’s alpha coefficient (threshold > 0.6) and the composite reliability (threshold > 0.6). Both measures demonstrate satisfactory values, with a Cronbach’s alpha of 0.960 and composite reliability of 0.974. Some researchers mention upper thresholds of 0.95 for both metrics, which could suggest redundant items. We have adopted the construct of adoption intention (*AIN*), along with its three indicators from previous studies that do not indicate any limitations (see, e.g., Cimperman et al. (2016); Baudier et al. (2020); Sequeiros et al. (2021); Große-Kreul (2022)). Regarding *convergence validity* in reflective measurements, the correlation between a measure and a comparable measure of the

same construct is assessed through the average variance extracted (AVE). A value greater than 0.5 is generally considered satisfactory, indicating that the construct explains approximately 50% of the variance in its indicators. We find a high value of 0.926. *Discriminant validity* refers to the degree to which a construct is genuinely distinct from other constructs, indicating the uniqueness of the construct within the model. The Heterotrait-Monotrait (HTMT) ratio measures this metric. Our model comprises only one reflective construct, so we could not determine the discriminant validity using the conventional HTMT ratio. At the bottom of Table 4.4, we report the loading on the intention to adopt SH (*AIN*) construct.

4.4.2 Results for the structural models

Before reporting the results of the regression models (A) and (B), we provide information on the results' validity and the models' explanatory power. Regarding *collinearity*, we observe that all VIF values of the inner model are below the cautious threshold of 3.3, indicating no collinearity problems. Looking into model (A), the comfort construct (*COM*) exhibits the highest VIF value with 2.267. In model (B), the performance expectation (*PEX*) construct has the highest VIF value of 3.062. These findings show that our model meets the collinearity thresholds suggested for PLS-SEM analyses. Considering *explanatory power*, model (B), which represents our principle variable of interest, has a satisfactory *R*-squared value of 0.571 and an adjusted *R*-squared value of 0.568, comparable to similar studies on SH adoption. Such studies generally fall into three categories. The first category employs a validated technology acceptance framework and shows *R*-squared values ranging from 0.610 (Baudier et al., 2020) to 0.820 (Große-Kreul, 2022). The second group comprises studies that rely on validated frameworks but adapt them to address specific research questions. Our research design is closest to these studies that report *R*-squared values ranging from 0.310 (Schill et al., 2019) to 0.540 (Wang et al., 2020). The third group includes studies that develop their model. Here, *R*-squared values range from 0.080 (Arthanat et al., 2019) to 0.426 (Tural et al., 2021). We note that including personal characteristics variables significantly enhances explanatory power, increasing the adjusted *R*-squared value from 0.386 to 0.568. This inclusion also improves the BIC value from -700.8 to -1 184.0. Note that we calculated BIC values for different model variations to control for overfitting. Additionally, we observe that model (A) exhibits an *R*-squared value of 0.640 and an associated BIC value of -1 508.0.

Model (A) for performance expectation In Table 4.5, we report the results of the regression model (A). It shows how perceived benefits related to comfort, safety, and health benefits are associated with performance expectation. The three benefits are significant for the overall perceived usefulness of the technology. Comfort considerations seem most relevant, followed by safety and health benefits.

Regression model (B) for adoption intention In Table 4.6, we present the results of the regression model (B), which demonstrates the association of the considered variables to the intention to adopt SH. Preventive health and safety benefits and comfort considerations are significantly associated with a greater intention to adopt. All three coefficients attain a significance level of 5%. Regarding personal characteristics, we observe that traits related to technology exhibit the strongest relationship with adoption intention. When combined with the user's gender, these features produce regression coefficients that, in absolute terms, exceed all the ones of the three benefits, highlighting their significance. Although the current literature

Hypothesis	Path		Coefficient	Sig.
<i>Prevention</i>				
(H1)	Safety	λ_{SAF}	0.295	***
"	Health	λ_{HEA}	0.229	***
<i>Comfort</i>				
(H3)	Comfort	λ_{COM}	0.389	***

Note: See Table 4.4.

Table 4.5: Results of regression model (A) for performance expectation.

focuses mainly on age as the primary attribute of an SH user, our findings show that the impact of frailty, homeownership, and cultural activity level is on par with that of age.

Hypothesis	Path		Coefficient	Sig.
<i>Prevention</i>				
(H2)	Safety	β_{SAF}	0.070	*
"	Health	β_{HEA}	0.068	**
<i>Comfort</i>				
(H4)	Comfort	β_{COM}	0.107	***
<i>Performance expectation</i>				
(H5)	Performance expectation	β_{PEX}	0.110	***
<i>Personal characteristics</i>				
(H6)	Technology affinity	β_{TAF}	0.273	***
"	Knowledge and preference	β_{KAP}	0.245	***
"	Age	β_{AGE}	-0.108	***
"	Gender (baseline: female)	β_{GEN}	0.218	***
"	Frailty (baseline: no)	β_{FRA}	-0.151	***
"	Homeownership (baseline: renter)	β_{HOW}	0.116	**
"	Cultural activity level (baseline: hardly ever)	β_{CAL}	0.061	**

Note: See Table 4.4.

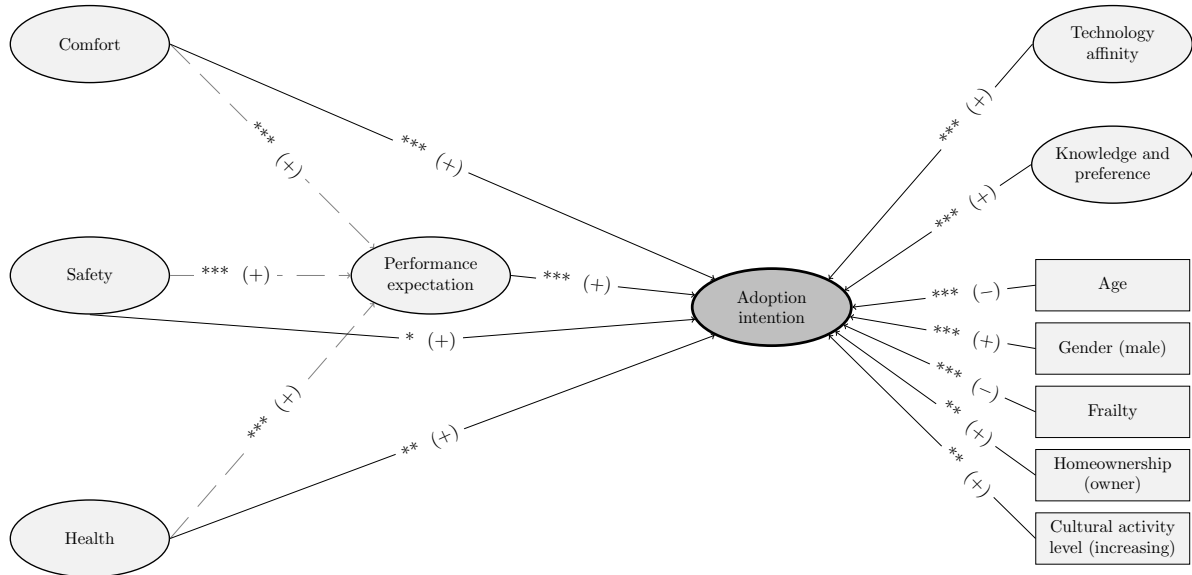
Table 4.6: Results of regression model (B) for adoption intention.

4.5 Discussion

Our study contributes to the risk and insurance literature by providing insights into users' perceptions of risk prevention benefits in the context of SH technology. Whereas wearable and telematic devices have received considerable research attention, SH technology has yet received less attention. Considering the potential for this technology to optimize risk behavior and enable real-time management, and with an increasing number of households using SH devices, the attention of risk researchers and practitioners is warranted. While previous research has shown that performance and convenience expectations positively influence the adoption of SH technology, we shed light on the extent to which risk prevention benefits play a role.

In Figure 4.2, the summarized results demonstrate the significance levels and regression coefficients, illustrating the strength and direction of variables' relationships with the intention to

adopt SH. Preventive health and safety benefits, alongside comfort considerations, are significantly connected to a higher intention to adopt SH, where comfort holds a greater impact than safety and health. Additional personal characteristics related to technology, sociodemographics, and active aging lifestyle also play a significant role in shaping adoption intention. Moreover, perceived benefits related to comfort, safety, and health are strongly associated with SH's overall performance expectation.



Note: See Table 4.4.

Figure 4.2: Model results, including coefficients' signs and significance levels.

Delving further into the importance of safety and health, our empirical results indicate that prospective SH users perceive technology as a viable tool to improve home safety and health. Safety-related SH products, such as fire alarms, security cameras, and water sensors, are commonly known to the public (Arar et al., 2021). Although personal characteristics and comfort considerations are most important for adoption intentions, safety also plays an important role. The literature also highlights some prevention use cases related to health (Chiu et al., 2020). While prior studies have often focused on individual diseases, we analyzed the perception of health-related benefits with adoption intention and safety preferences. Our findings indicate that health significantly affects these factors. This observation may be affected by the age of 45 years and older in our respondents, which is consistent with other research and indicates a greater interest in SH applications among older adults (Iten et al., 2024; Klobas et al., 2019).

User behavior is rarely emphasized or discussed in the context of SH. However, to fully realize the potential of SH technology for risk prevention, it may be necessary to encourage user engagement in SH prevention use cases. Such engagement can pave the way for insurers seeking to minimize risk and control claims costs. Working collaboratively with individuals to proactively implement risk mitigation measures through SH allows insurers to promote safety and health measures actively. Insurers can strengthen their relationship with policyholders by providing incentives for household prevention efforts, such as premium discounts or financial contributions towards acquiring and maintaining technology. Maintaining user engagement and compliance

with the indented service (e.g., keeping the SH devices turned on, changing batteries) is also crucial for the effective functioning of the technology and the management of emerging cybersecurity risks. Offering concierge and technical support services may give insurers a feasible strategy to boost customer engagement and expand their business model with risk-free service income.

The importance of comfort benefits concerning SH adoption is critical and consistent with previous research findings. The work of Chang and Nam (2021), conducted in the Republic of Korea, revealed similar patterns in the relative importance of comfort, health, and safety, with energy considerations found to be insignificant, implying that cultural differences may have a minor influence on these research results.

Finally, specific personality traits, such as age, gender, technology affinity, and knowledge, play critical roles in characterizing potential SH users. Additionally, previously unstudied variables like frailty, homeownership, and cultural activity level exert similar influences on adoption intention as, for example, age. The integration of these personality traits significantly improves the explanatory power of the model (ignoring the effect of these variables would reduce our explanatory strength to an adjusted R -squared value of 0.386), emphasizing the importance of tailored market segmentation for SH users with a focus on prevention-related features.

4.6 Conclusion

This work investigated prevention benefits in the context of Smart Home (SH) adoption and empirically derived to what extent users perceive the value of prevention in technology. We identified and established clear links between the prevention benefits associated with safety and health and the intention to adopt SH technology. Furthermore, we confirmed a significant and positive relationship between the comfort benefits of SH and the increased interest in the technology. We also provide a set of personal characteristics variables that describe the individuals attracted to the SH prevention premise.

Practitioners and policymakers may find the results helpful. In particular, insurers interested in leveraging SH technology for innovative technology-driven service models can benefit from the established evidence. First, it is essential to contextualize the value proposition for safety and health benefits within the broader range of user comfort and performance expectations. Focusing solely on preventative aspects may have an adverse effect when users perceive the technology as overbearing or patronizing. Regarding market segmentation, the data suggest that homeowners and active individuals represent promising target groups. Marketing strategies for prevention-oriented SH solutions could thus be tailored accordingly. Linking SH solutions with an active lifestyle could be a promising approach. Thirdly, the findings indicate that a lack of knowledge and affinity for technology could pose significant obstacles to dissemination, thus necessitating the provision of offers such as concierge or support services to mitigate such barriers.

Although we advance our understanding of SH's potential in terms of prevention, inherent limitations due to the self-reported nature, limited knowledge of some respondents, lack of time dimension, and geographic focus of the data set limit the scope and generalizability of our findings. While we focused on the direction and significance of the hypothesized relationships and on maximizing the explained variance of the model, we did not explore the effect sizes of

the key variables. This further limits our ability to assess the strength and economic impact of these relationships. Future research could benefit from controlled experiments or observations of purchase and usage behavior to bridge the gap between stated adoption intentions and actual smart home adoption and risk prevention behaviors.

4.7 Appendix

Survey data examination

Examination	Description
Missing data handling	With less than 5% missing values for each variable, we applied the mean replacement technique where needed. Across all variables, there were a total of 48 missing values. The variable sense of safety (<i>SOS</i>) has the highest number of missing values (20 values, 1.3%).
Suspicious responses	The original survey included screening questions, quality checks, and a randomization process to reduce the number of suspicious responses. Upon examination of the distribution and variance of the responses, we excluded two participants over 90 years of age from the sample.
Outliers	Using the Mahalanobis distance, we reveal missing values in the indicators <i>IUS</i> , <i>PUS</i> , and <i>OUS</i> related to the variable <i>AIN</i> . We exclude the 11 responses that show missing values in the three indicators.
Data distribution	The data distribution analysis for skewness and kurtosis reveals no critical values. We observe that the variable <i>GEN</i> has a kurtosis of -2.003 .
Common-method bias	Assessing the VIF values of the inner model and those obtained from the random variable approach, we find that all variables that appear in the final model show VIF values significantly below the 5.0 threshold and even below the more cautious 3.3 threshold.

Table 4.7: Details on the examination of the survey data.

Stepwise variable selection in regression model (B)

Round	Model	Extension	Coeff.	Sig.	Adj. R^2	BIC	Non-sig. variable	Inner VIF	Outer VIF
0	Base*		na.	na.	0.386	-700.8	None	OK	OK
1	Base	<i>TAF</i>	0.385	0.000	0.505	-1019.7	None	OK	OK
2	Round 1	<i>KAP</i>	0.284	0.000	0.543	-1131.3	None	OK	OK
3	Round 2	<i>GEN</i>	0.196	0.000	0.551	-1153.1	None	OK	OK
4	Round 3	<i>AGE</i>	-0.096	0.000	0.560	-1175.7	None	OK	OK
5	Round 4	<i>FRA</i>	-0.119	0.004	0.562	-1176.6	None	OK	OK
6	Round 5	<i>HOW</i>	0.112	0.001	0.565	-1179.5	None	OK	OK
7	Round 6	<i>CAL</i>	0.061	0.001	0.568	-1184.0	None	OK	OK

Notes: The columns ‘‘Coeff.’’ and ‘‘Sig.’’ refer to the regression coefficient and significance (p value) for the added variable named in the column ‘‘Extension’’. The column ‘‘Non-sig. variable’’ indicates whether any of the regression coefficients of the variables results in a significance level (p -value) worse than 5% when the extension is added. The last columns (‘‘Inner VIF’’ and ‘‘Outer VIF’’) indicate whether any variable exceeds the VIF threshold 3.3. *The ‘‘base model’’ refers to the model that only includes the variables *COM*, *SAF*, *HEA* and *PEX* as described in Section 4.3.3. The abbreviation ‘‘na.’’ stands for ‘‘not applicable’’.

Table 4.8: Performance results for intermediate models in the stepwise variable selection procedure in regression model (B).

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Chapter 5

Insurance in the Digital Age: On the Drivers of Smart Home Insurance

Using Internet of Things (IoT) technology in home insurance offers significant opportunities to improve service and product development and enhance risk management practices. Previous studies have shown that new factors emerge in the insurance sector that shape the demand for IoT applications. This study analyzes a comprehensive smart home data set in Switzerland to determine the critical factors generating interest in smart home insurance (SHI). Econometric and machine learning methods are employed to identify the key variables impacting consumer behavior in the specific insurance technology landscape under investigation. We find that incentives for insurance customers are a crucial factor in increasing interest in SHI. This includes reimbursement for smart home device purchases and adjustments in insurance premiums. Additionally, effective prevention services offered by insurers have been identified as another driver for increased SHI interest. On the other hand, perceiving smart home technologies as non-essential luxuries acts as a barrier. Factors related to an individual's characteristics are secondary in the decision-making process, apart from their willingness to share data with an insurer. Our results provide a basis for a deeper understanding of the evolving field of smart home insurance, which is less established than similar developments in health and car insurance. The implications of our research are relevant beyond the academic community and are of interest to individuals and insurers alike.

Note: This is a joint work with J. Wagner and A. Zeier Röschmann. The authors would like to thank the PhD students of the DSA-HEC Lausanne for their feedback on previous versions of this manuscript.

5.1 Introduction

Internet of Things (IoT) technologies have transformed customer expectations and insurance business models. Market developments are evident in the home insurance sector through connected devices, the car insurance sector through telematics, and the health insurance sector through wearables. IoT offers a range of possibilities for insurance, including the ability to provide real-time risk monitoring capabilities and to encourage policyholders to engage in less risky behaviors (Flückiger and Carbone, 2021). While considerable research has been conducted on the impact of telematics (Meyers and Hoyweghen, 2020; Ziakopoulos et al., 2022) and wearables (Saliba et al., 2022; Soliño-Fernandez et al., 2019) in insurance, insights into smart home insurance are still limited. In this paper, we define smart home insurance (SHI) as insurance solutions that address the (enhanced) possibilities of managing and financing risks in a home with the support of interconnected devices and sensors. Risks include damages from traditional insurance risks such as fire, water, or theft, emerging risks related to cyber security or privacy breaches, and issues with technology performance at home (Iten et al., 2021). The concept of SHI aligns with the broader trajectory of IoT applications that offer risk management features (Zeier Röschmann et al., 2022).

As the market for smart home devices and solutions continues to evolve, it is essential to understand user interest in SHI. Research on insurance demand suggests that economic, social, and cultural factors are among the most important factors that shape decision-making (Outreville, 2013). However, recent research on the demand for IoT-enabled insurance has revealed new aspects, such as incentive mechanisms, available support services, prior experience with IoT technology, and concerns about privacy (McFall, 2019; Milanović et al., 2020). Notably, many studies exploring the success of new technologies use technology acceptance models. These works build upon Davis' (1989) proposal to study the influence of factors such as perceived usefulness and ease of usage on the intention to use new technologies. In light of the growing role of the IoT, we argue that current knowledge on insurance adoption should be reviewed.

This research aims to better understand the factors that drive interest in IoT-enabled insurance, focusing on SHI. To this end, our research question asks what the key factors influencing interest in SHI are. Our analysis uses 65 predictor variables related to SHI demand, a subset of the variables collected in a recent survey on users' interest in smart homes carried out in Switzerland. We employ both classical regression and machine learning techniques. A stepwise selection algorithm based on Akaike's information criterion in logistic regression was used to identify the most significant variables for SHI interest, and the importance of the retained variables was ranked using a log-likelihood ratio test. Additionally, a random forest model was used to conduct recursive feature elimination and cross-validate the results obtained from the regression and rankings.

Our empirical results offer insights into the factors influencing interest in SHI. The individual willingness to share data with the insurer is one of the critical factors. Additionally, reimbursing costs associated with purchasing smart home devices is central to generating interest. Financial incentives such as these can increase interest in SHI, as demonstrated by the importance of two other factors related to the adjustment of insurance premiums. Our analysis further shows that the insurer's provision of suitable prevention services can increase interest in SHI. On the

other hand, the perception of smart home technologies as a non-essential luxury is negatively associated with SHI interest. We also identify personality traits that affect interest, such as a preference for health-related applications, being a technology experimenter, and regional residency. Integrating IoT technologies into current insurance practices creates new expectations from policyholders beyond traditional financial compensation. Understanding how these new expectations affect consumer behavior is central for insurers to leverage IoT's potential for risk prevention effectively.

The article is structured as follows. In Section 5.2, we examine the literature on insurance demand and the impact of IoT on the insurance industry to guide our research endeavor. Section 5.3 presents the available data and methodology used to analyze the drivers of interest in SHI. Results are displayed in Section 5.4. In Section 5.5, we discuss our findings, and we conclude in Section 5.6.

5.2 Theoretical background

This section reviews the literature on the drivers of insurance demand and discusses the impact of IoT technologies on insurance. It also outlines current market developments. Additionally, we present the research hypotheses. Our hypotheses are based on a literature review of the drivers of insurance demand and the impact of IoT on insurance, incorporating both theoretical papers and empirical studies.

5.2.1 Insurance demand

The relationship between the demand for non-life insurance and various factors has been studied extensively. These factors include economic development (Trinh et al., 2020), income (Beck, 2003), demographic factors (Park and Lemaire, 2012), household characteristics (Millo and Carmeci, 2011), as well as behavioral aspects such as risk aversion and behavior (Outreville, 2014) or emotions and psychological traits (Brighetti et al., 2014). However, research has also shown that life insurance and individuals have received more attention than non-life or the corporate sector (Outreville, 2013). Outreville (2013) identified four major groups of macroeconomic factors influencing insurance demand in a review of 85 empirical papers. These factors include economic, demographic, social, and cultural variables, as well as institutional or market-related variables. Based on these four factors, Trinh et al. (2016) conducted a study that provides additional empirical evidence to non-life insurance demand. They demonstrate that economic freedom and per capita income positively impact non-life insurance expenditure in developed countries. Other factors influencing insurance expenditure include bank development, urbanization, individualism, masculinity, power distance, and hypometropia, while education negatively affects insurance demand.

Studies that use disaggregated data to differentiate between insurance lines report varying results. Brighetti et al. (2014) examined how psychological variables expand the neoclassical understanding of the drivers of insurance demand. According to the survey, the authors found that demand for indemnity insurance is driven by fear of the unknown, while emotional arousal to losses is a stronger predictor for casualty insurance. Browne et al. (2000) suggest that there are differences between motor vehicle and general liability insurance and that income has a far more significant effect on motor vehicle insurance consumption. Barseghyan et al. (2013)

and Sydnor (2006) analyzed households' choice of deductibles to measure the influence of risk aversion. Both found that risk aversion is higher in new homeowners insurance than in motor vehicle insurance.

The demand for non-life insurance is influenced by a range of determinants. Our first hypothesis aims to validate whether the economic, demographic, social and cultural, and structural variables identified by Outreville (2013) that influence general insurance demand also influence the demand for smart home insurance offerings.

(H1) *The determinants of insurance demand influence the intention to adopt SHI.*

5.2.2 Impact of IoT on insurance

Flückiger and Carbone (2021) study provides valuable insights into the potential of IoT technologies for insurers. The study demonstrates the capabilities of IoT in predicting, preventing, and mitigating risks and discusses how IoT empowers insurers with real-time risk monitoring and the ability to encourage less risky behaviors. In household insurance, interconnected devices and sensors are used to proactively monitor and manage risks, aligning with the broader trend of IoT applications for risk prevention and enhanced customer experiences (Braun et al., 2023; Iten et al., 2024; Zeier Röschmann et al., 2022). In car insurance, telematics uses IoT devices to monitor driving behavior and create new insurance offers based on real-time data (Ho et al., 2022). Wearables track various health-related metrics in health insurance, providing insurers with insights to tailor services for health promotion and disease prevention (Soliño-Fernandez et al., 2019).

Empirical evidence suggests that IoT applications can potentially reduce loss experience. For telematics, Denuit et al. (2019) and Qazvini (2019) have demonstrated tangible benefits in reducing the likelihood of claims. Ziakopoulos et al. (2022) conducted a systematic literature review that quantifies the positive impact on road safety. Sixteen out of twenty-one studies reported tangible improvements resulting from reductions in road crashes, speeding incidents, and harsh events. However, a study by Meyers and Hoyweghen (2020), which accompanied the launch of a Belgian insurance telematics initiative, produced inconclusive evidence of the desired relationship between driving behavior and claims cost reduction. The literature also suggests that advances in the IoT are driving a trend toward segmentation and personalization in insurance (Kalouguina and Wagner, 2023). Meyers and Hoyweghen (2018) discuss the evolution of actuarial fairness in the insurance industry over time and how this concept is used to justify discrimination between risk groups. Kuryłowicz and Sliwiński (2022) show that continuous risk monitoring could reduce adverse information asymmetry effects by increasing the potential for self-selection. Ostrowska (2021) envisions a shift that could potentially eliminate the need for traditional risk declarations.

Recent literature further discusses several drivers that impact interest in IoT-enabled insurance. Across different use cases, incentive mechanisms, availability of services, and privacy concerns are pointed out. In telematics, Tian et al. (2020) validated an adoption model based on 15 identified telematics technology studies. They found that ease of technology usage is the critical factor for increased interest in insurance. Milanović et al. (2020) find that the availability of support services from insurance carriers is the main predictor of future usage. In addition,

Kuryłowicz and Sliwiński (2022) observe a negative relationship between interest in telematics-based insurance and factors such as distance traveled and premium value, suggesting a potential self-selection mechanism in the assignment of risk profiles. Soliño-Fernandez et al. (2019) highlight the importance of economic incentives in influencing individuals' willingness to adopt wearables for insurance purposes. Similarly, other empirical studies show that monetary incentives positively influence the policyholders' behavior (Mortimer et al., 2018; Reagan et al., 2013). Saliba et al. (2022) study sports-related wearables and highlight that individuals' perceptions of usefulness and prior technology experience are critical determinants of adoption. Privacy concerns regarding the inappropriate handling of personal user data collected from the IoT system are a major factor for adoption across wearables (Soliño-Fernandez et al., 2019) and telematics (Milanović et al., 2020).

The study by LexisNexis Risk Solutions (Davis, 2020) is one of the first to focus on SHI. The study found that nearly half of the respondents who owned at least one smart home device would purchase more if incentivized through insurance discounts. The authors further note that interest in SHI offerings increases with recent claims experiences that could have been addressed with a smart device. Although awareness of SHI initiatives remains limited, 75% of current smart home device owners are willing to share data with insurers if privacy concerns are addressed. (Davis, 2020)

The integration of IoT technologies into insurance applications has introduced new factors influencing insurance demand. Studies on telematics (Milanović et al., 2020) and wearables (Soliño-Fernandez et al., 2019) highlight that technology adoption factors, such as incentive mechanisms, service availability, as well as privacy concerns, and certain personality traits, significantly impact consumer interest. Our second hypothesis therefore aims to validate whether these same factors influence the demand for smart home insurance offerings.

(H2) *IoT adoption factors influencing other insurance applications extend to SHI adoption.*

5.2.3 Market overview of smart home insurances

To illustrate the characteristics of SHIs, we present a selection of SHI offerings in the European and American private customer markets. Table 5.1 displays the insurance company's name, the market, and a short offer description. Additionally, we identify the main components of the offer, including the household risks covered, whether the offer is considered a new and stand-alone policy or a premium discount on an existing policy, and whether financing options are available for smart home devices.

We categorize insurance companies as either traditional companies or InsurTech companies, where the latter are companies that self-identify as startups. In our market study, we found more offers from traditional insurers and US-based insurers. Regarding the risks covered, each offer tends to address multiple risks. Geographical differences are noticeable in the emphasis placed on specific issues. The US market prioritizes security concerns, while the European market focuses on water-related risks. Regarding policy design, we observe that SHI offerings usually provide premium discounts on existing household premiums and partial funding for smart home products. Providers often do not disclose specific details about premium discounts. Still, they emphasize individual premium considerations and the effectiveness of the monitoring

system to ensure the functionality of smart home sensors. Most offers analyzed provide partial reimbursement, while only some provide full reimbursement of smart sensor costs. Overall, there are varying approaches among insurance companies. For example, Branch Insurance offers a discount of up to 15.5% while Sky Protect markets its offer as a lifestyle product with higher premiums than its existing home insurance products.

Overall, we note the prevalence of incentive mechanisms in current SHI offers. This aligns with the earlier observations on the impact of IoT on insurance demand (see Section 5.2.2). Other aspects, such as individualization or segmentation, are less observable. For instance, Goosehead Insurance actively promotes individualized insurance consulting services, while Nationwide offers higher reimbursement to homeowners than renters. Further, Sky Protect incorporates IoT parameters to attract tech-savvy customers.

5.3 Method and data

This section presents an overview of the data and methodologies used to investigate our research question and test the hypotheses formulated in the previous section. Firstly, we describe our data set and all variables considered in the analysis, with particular emphasis on the primary variable of interest, the interest in a SHI offering. Then, we describe the regression and random forest models used to explore the data.

5.3.1 Available data and variables

Data set The analysis is based on a cross-sectional survey conducted in Switzerland in 2022 (Iten et al., 2023). The data is organized into four categories: personality traits of respondents, risks and costs of smart home insurance offerings, evaluation of the technology’s prevention benefits, and adoption dimensions of smart home technology usage. For this analysis, we considered the groups of personality traits and variables related to smart home insurance, resulting in a subset of 67 variables. These variables cover individuals’ expectations of an insurance-linked smart home offering and the participants’ characteristics. Variables related only to the perception and adoption of smart home technology were excluded as they missed the insurance link. The data set comprises 2 490 observations of individuals aged 45 years and older, with quotas for gender, Swiss language region, and knowledge of smart home technology (Iten et al., 2024). We assess the data quality using a multi-step framework outlined by Hair et al. (2010, Chap. 2). To mitigate the impact of suspicious responses, the survey included screening questions and quality checks. These control measures indicate that 973 responses were invalid (see also, Iten et al. 2024, Section 3.1 and Appendix C). Upon closer examination, an additional 2 suspicious responses were discovered among participants over ninety years of age, leading to the removal of 975 records from the sample. Outliers were also addressed using the Mahalanobis distance method, which revealed four missing values in the two indicator variables related to the dependent variable, interest in a health insurance offering (*IIN*). A total of 118 missing values were observed across all variables, with the highest numbers observed in the variables voluntary work (*VWO*, $N = 19$), club activity level (*CAC*, $N = 9$), and discount on insurance premium (*DOI*, $N = 8$). Although the percentage of missing values for each variable was less than 5%, these records were excluded from the sample. The distribution of the data was analyzed for skewness and kurtosis. After removing all records with missing values, no outliers were left. The highest

Smart home insurance company	Country	Description of the offer	Water	Fire	Hall	Break-in	Lost item	Energy	Home care	New and stand-alone policy	Premium discounts on existing policy	Smart sensor purchase refund option
<i>Traditional insurance companies</i>												
Building Insurance Berne ^a	CH	Discounted smart home sensors for added protection.	✓	✓	✓	✓	✓	✓		No	None	Partial refund
Cantonal Building Insurers ^b	"	Free hail-triggered automatic blind system for added security.		✓						No	None	Full refund
Generali ^c	IT	Free sensor bundle designed to prevent multiple home risks.	✓	✓	✓	✓				No	None	Partial refund
Allstate ^d	US	Professional home security monitoring system.			✓	✓	✓			No	Up to 5%	None
American Family ^{e,f}	"	Free sensor bundle designed to prevent multiple home risks.	✓	✓	✓	✓	✓			No	Unspecified	Partial refund
Amica Mutual ^g	"	Discounted smart home sensors for added protection.	✓	✓	✓	✓	✓			No	Unspecified	Partial refund
Goosehead Insurance ^h	"	Individualized insurance coverage based on own technology setup.	✓	✓	✓	✓	✓	✓		Yes	None	Partial refund
Liberty Mutual ⁱ	"	Incentives for home maintenance and discounted smart home sensors.	✓	✓	✓	✓	✓	✓	✓	No	Unspecified	Partial refund
Nationwide ^j	"	Professional monitoring targeted at water and fire risks.	✓	✓						No	5% for smoke, 10% for water	Based on home ownership
State Farm ^{k,l}	"	Professional home security monitoring with installation and repair credits.	✓	✓	✓	✓	✓			No	Up to 6%	Full refund
USAA ^{m,n}	"	Combination of discounted sensors and professional home security monitoring.			✓	✓	✓			No	Unspecified	Partial refund
VYRD ^o	"	Combination of discounted sensors and professional home security monitoring.	✓	✓	✓	✓	✓			No	Up to 15%	None
<i>InsurTech companies</i>												
Enzo Homeowner Insurance ^p	DE	Discounted main water pipe sensor for leak detection.	✓							No	None	Partial refund
Sky Protect ^q	UK	Free sensor bundle designed to prevent multiple home risks.	✓	✓	✓	✓	✓	✓		Yes	None	Full refund
Branch Insurance ^r	US	Combination of discounted sensors and professional home security monitoring.	✓	✓	✓	✓	✓			No	Up to 15.5%	Full refund
Hippo ^s	"	Combination of discounted sensors and professional home security monitoring.	✓	✓	✓	✓	✓			No	From 10-13%	None
Honey ^t	"	Free sensor bundle designed to prevent multiple home risks.	✓	✓	✓	✓	✓			No	Up to 8%	Full refund

Note: InsurTech companies are entities that self-identify as startups. Energy and home care do not pose inherent risks but indicate whether the offer fulfills the corresponding additional service promises. See Footnote 1 for the name of the smart home insurance offering (notes ^a to ^t).

Table 5.1: Selection of smart home insurance offerings, risks addressed, and insurance design features.

kurtosis was observed in the gender variable (*GEN*) at -2.003 . This rigorous analysis ensures the reliability of the study data, and we retain a final sample of $N = 1\,397$ responses.

Available variables Our primary variable, “interest in a SHI offering” (*IIN*), is based on two items. The items were contextualized within the following scenario: “*Suppose you could get smart home services from an insurance company. The insurance company provides such services because they prevent accidents and contribute to home security. However, this implies a willingness to share data with the company.*” Participants indicated their agreement with the two following statements on a five-level Likert scale ranging from “strongly disagree” to “strongly agree”:

- I intend to use a smart home insurance offering in the future.
- Given the chance, I plan to use a smart home insurance offering in the near future.

We illustrate the distribution of the responses in Figures 5.1(a) and 5.1(b) in the Appendix. We construct the binary latent variable *IIN* based on the two statements. We use a numerical scale ranging from one to five for the original responses and determine the mean level of agreement with both statements. A score higher than three is interpreted as a “yes.” The obtained Cronbach’s alpha coefficient of 0.847 shows a high degree of internal consistency in our sample, indicating reliability. Only 4% of the respondents, which corresponds to 56 responses, showed relevant discrepancies in their responses to the two statements. This emphasizes the consistency of the responses (see Figure 5.3 in the Appendix). Overall, we find that 41% of the total sample expressed interest in SHI.

In the following, we present the predictor variables used in our study. To validate our hypotheses, we have categorized these variables into four themes, aligning with the theoretical background. Each theme is subsequently described, with a focus on illustrating their connections to the hypotheses derived from the insurance demand literature (H1) and technology adoption literature (H2).

Importance of SHI incentives and costs. Given the importance of economic factors in shaping insurance demand, and the significant role of incentive mechanisms in driving the adoption of other IoT insurance applications, we considered several variables to measure the impact of incentives and costs on the adoption of SHI. We included participants’ expectations regarding discounts on insurance premiums (*DOI*), interest in automatic premium adjustments (*APA*), expectations for reimbursement of purchase costs (*ROP*), and expectations of behavior change incentives from the insurer (*BCH*).

Importance of SHI services. Recognizing that the availability of support services is crucial for IoT technology adoption and that structural variables in the insurance demand literature highlight the importance of such developments, we examine the importance individuals place on various services potentially offered by SHI. For that, variables like advice from the insurer

¹Smart home insurance offerings underlying Table 5.1: ^aGVB Smart Home, ^bHail protection - simply automatic, ^cJenIoT, ^dCanary Security Cameras, ^eHedge Protect, ^fADT Pulse, ^gSmarter Home Savings, ^hVivint Insurance, ⁱLiberty Plus, ^jNationwide Smart Home, ^kADT Pulse, ^lTing Fire, ^mADT Pulse, ⁿUSAA Connected Home, ^oVYRD Smart Home Water Protection, ^pEnzo, ^qSky Protect Smart Home Insurance, ^rSimpliSafe Sensors, ^sHippo Smart Home, ^tSmarter Home Insurance. The information was retrieved from the company websites in January 2024.

(*AFI*), early warnings on potential risks (*EWF*), individualized offers matching personal interests (*IOF*), and the willingness to share data with the insurer (*SDW*) are examined.

Concerns regarding SHI technology. Our analysis furthermore includes potential concerns related to SHI technology, particularly data misuse (*DMI*) and unforeseeable use of collected data (*DUF*). These concerns are critical given the central role that privacy considerations play in influencing the adoption dynamics of IoT technology. We also address perceived dependence on technology (*DEP*) and loss of control over technology (*LOC*), as well as two variables related to the cumbersomeness of usage (*OVE* and *CUM*). Additionally, we examine concerns about costs, including worries about costs exceeding benefits (*CEB*), concerns about expensive maintenance (*EMA*), and the perception of smart home technology as a non-essential luxury (*NEL*). Two variables address fears related to the security of SHI technology (*SOP* and *INS*). Three variables cover social aspects, such as concerns about going less out of the house (*GLO*), technology to replace contact with others (*RCW*), or concerns about a lack of human interaction (*LOH*).

Personality traits. Finally, we included a set of personal characteristics that may be associated with greater interest in SHI. These variables aim to provide a comprehensive profile of an interested individual, drawing on demographic, social, and cultural variables known to influence insurance demand decisions, as well as traits common among early adopters of IoT insurance applications. For the latter, we included variables related to technology affinity and knowledge as well as preferences regarding smart home technology. In the case of the former, variables related to economic aspects, socio-demographic background as well as social and cultural aspects are included. Additionally, details on the insurance portfolio of the respondents are provided.

In Table 5.2, we show the complete set of retained variables, including their thematic focus, description, and possible values.

Sample distribution Table 5.3 presents the distribution of our final sample across various socio-demographic variables, assessing its representativeness compared to data provided by the Swiss Federal Statistical Office (2024). Compared to population statistics, we show a slight overrepresentation of the 65–74 age group, a balanced gender distribution, and a similar distribution of disposable income. The sample does not represent the Italian-speaking region and slightly overrepresents individuals with a high school education. Additionally, there is a relatively high prevalence of homeownership.

5.3.2 Methodology

Our methodological framework combines regression and random forest techniques to explore the factors influencing interest in SHI. The analysis was performed within the R software environment, utilizing the `MASS`, `caret`, and `randomForest` packages. The following paragraphs present the methodology employed to determine a subset of variables that significantly enhances the understanding of interest in SHI. A classification framework is appropriate since the interest in a SHI offering (*IIN*) is the dependent variable. This approach focuses on the binary outcome of whether an individual expresses interest in SHI.

Variable	Label	Description	Categories
<i>Interest in smart home insurance offering</i>			
<i>IIN</i>	Interest in a SHI offering	Intention to use a SHI offering in the future	No, yes
<i>Importance of smart home insurance incentives and costs</i>			
<i>DOI</i>	Discount on insurance premium	Expect to receive discount on insurance premium	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>
<i>APA</i>	Automatic premium adjustment	Expect price of insurance to adjust automatically	"
<i>ROP</i>	Reimbursement of purchase costs	Expect insurer to cover cost of purchase	"
<i>BCH</i>	Behavior change	Expect insurer to give incentives for appropriate behavior	"
<i>Importance of smart home insurance services</i>			
<i>AFI</i>	Advice from insurer	Expect insurer to provide advice on home maintenance	"
<i>EFW</i>	Early warning from insurer	Expect insurer to give early warning on incipient risks	"
<i>IOF</i>	Individual offers from insurer	Expect insurer to provide offers that match personal interests	"
<i>SDW</i>	Share data with insurer	Expect to share data from smart home with insurer	"
<i>Concerns regarding smart home insurance technology</i>			
<i>DMI</i>	Data misuse	Concern of collected data being misused	"
<i>DUF</i>	Data used unforeseeable	Concern of collected data being used unforeseeable	"
<i>DEP</i>	Dependence	Concern of increasing dependence on technology	"
<i>LOC</i>	Loss of control	Concern of losing control of technology	"
<i>OVE</i>	Overwhelming	Concern of overwhelming technology usage	"
<i>CUM</i>	Cumbersome	Concern of cumbersome technology usage	"
<i>CEB</i>	Costs exceeding benefits	Concern of costs exceeding benefits	"
<i>EMA</i>	Expensive maintenance	Concern of expensive maintenance	"
<i>NEL</i>	Non-essential luxuries	Concern of turning into a non-essential luxury	"
<i>SOP</i>	Source of problems	Concern of leading to problems	"
<i>INS</i>	Insecure	Concern of being insecure	"
<i>GLO</i>	Go less out of house	Concern of less going out of the house	"
<i>RCW</i>	Replace contact with others	Concern of replacing contact with others	"
<i>LOH</i>	Lack of human interaction	Concern of resulting in lack of human interaction	"
<i>Personality traits</i>			
<i>TEX</i>	Technology experimenter	Pleasure in trying new technologies	"
<i>TPI</i>	Technology pioneer	First to try new technologies	"
<i>TXT</i>	Technology expert	Skills in using smartphone or tablet	Five levels from <i>poor</i> to <i>excellent</i>
<i>MAV</i>	Mistake avoider	Potential errors discourage from usage	Five levels from <i>strongly disagree</i> to <i>strongly agree</i>
<i>FPR</i>	Familiarity preferer	Familiar things are preferred over new ones	"
<i>RTL</i>	Risk-taking level	Self-assessed preferences for risky behaviour	Five levels from <i>not at all</i> to <i>very willing to take risks</i>
<i>KLE</i>	Knowledge level	Level of experience in smart home technology	Five levels from <i>no</i> to <i>very good knowledge</i>
<i>CAP</i>	Convenience application	Preferences for sensors serving convenience purposes	Five levels from <i>dislike</i> to <i>like</i>
<i>HAP</i>	Health application	Preferences for mobile health device	"
<i>LAN</i>	Survey language	Chosen language of the questionnaire	German, French
<i>AGE</i>	Age	Age class in years	45–54, 55–64, 65–74, 75+ (from numeric answers)
<i>GEN</i>	Gender	Gender of the respondent	Female, male, diverse, prefer not to reply
<i>EDU</i>	Education	Highest level of education	Mandatory school, high school, higher education
<i>ISU</i>	Income sufficiency	Income sufficiency for recurring expenses	With great difficulty; with some difficulty; fairly easily; easily
<i>ECA</i>	Expense capacity	Ability to cover an unexpected expense	No, yes
<i>PSI</i>	Professional situation	Current employment situation	Retired, employed, unemployed, homemaker, unable to work
<i>HOW</i>	Home ownership	Main residence ownership	Rent, ownership
<i>MAR</i>	Marriage/partnership	Living with spouse/partner in a household	No, yes
<i>SHO</i>	Single household	Living alone (without anyone else)	"
<i>HWK</i>	Household with kid(s)	Living with kids in one household	"
<i>OHO</i>	Other households	Living in other household constellation	"
<i>MSA</i>	Mildly strenuous activities	Physically mildly strenuous activities	Hardly ever, 1-2x month, 1x week, >1x week
<i>RSA</i>	Really strenuous activities	Physically really strenuous activities	"
<i>FRA</i>	Frailty	Frailty in certain everyday activities	No, yes
<i>SWL</i>	Satisfaction with life	Satisfaction with current life situation	Five levels from <i>completely dissatisfied</i> to <i>completely satisfied</i>
<i>DSY</i>	Depressive symptoms	Feeling sad or depressed	No, yes
<i>LON</i>	Loneliness	Feeling lack of companionship	Almost never or never, 1-2x month, 1x week, >1x week
<i>CAL</i>	Cultural activity level	Participation in cultural activities	Hardly ever, few times a year, 1-2x month, 1x week, >1x week
<i>GSI</i>	Group sports involvement	Participation in group sports	"
<i>ECO</i>	Educational courses	Participation in educational courses	"
<i>VWO</i>	Voluntary work	Participation in voluntary work	"
<i>CAC</i>	Club activity level	Participation in club activities	"
<i>OLE</i>	Outgoing level	Going out with friends	"
<i>AGR</i>	Active grandparent	Looking after grandchildren	"
<i>SHA</i>	Suppl. health insurance	Supplementary health insurance	No, yes
<i>MVI</i>	Motor vehicle insurance	Motor vehicle insurance	"
<i>TIN</i>	Travel insurance	Travel insurance	"
<i>LIN</i>	Liability insurance	Liability insurance	"
<i>LIF</i>	Life insurance	Life insurance	"
<i>HIN</i>	Household insurance	Household insurance	"
<i>LEI</i>	Legal expenses insurance	Legal expenses insurance	"
<i>OIN</i>	Other insurance	Other less frequent insurance contracts	"
<i>IAI</i>	Insurance app in use	App from any insurance company in use	"

Table 5.2: Overview of the variables with description and possible values.

Given the high number of variables and the relatively limited number of observations, we reduce the number of coefficients estimated in the model by aggregating the levels of all variables measured on a five-level Likert scale into three categories. Thereby, the opinions “strongly disagree” and “disagree” (“agree” and “strongly agree”, both “dislike” levels, both “like” levels) are gathered in the single category “disagree” (“agree”, “dislike”, “like”). This guarantees a parsimonious handling of the predictor variables while retaining the essential information captured by the original scale.

	Sample		Sample		Sample
Age		Income sufficiency		Education	
45–54 years	30.6	With great difficulty	5.0	Mandatory school	3.1
55–64 years	29.8	With some difficulty	27.7	High school	63.9
65–74 years	30.3	Fairly easily	49.2	Higher education	33.0
75+ years	9.4	Easily	18.1		
Gender		Survey language		Home ownership	
Female	50.5	German	66.8	Renter	51.7
Male	49.5	French	33.2	Owner	48.3

Notes: The reported values are the sample shares in % per characteristic ($N = 1397$).

Table 5.3: Survey sample characteristics.

Logistic regression Following the variable preparation, we fit a logistic regression model to the data. To begin with, we use the full set \mathcal{R} of 65 variables (see Table 5.2) and choose the logit link function over the probit link function for its suitability in binary outcome models and its better performance in terms of the Bayesian Information Criterion (BIC, logit: 1648.6, probit: 1652.8). To find the determinants of the response variables IIN , we then employ a forward and backward stepwise selection using the BIC as the measure of model fit. The forward procedure iteratively refines the model, including only the variables that contribute significantly to explaining the variation in the variable IIN (BIC: 1103.5). Let $\mathcal{R}' \in \mathcal{R}$ be the subset of the nine retained predictor variables. Equation (8) represents the regression model across all responses i ,

$$g(IIN_i) = \beta_0 + \sum_{\mathbf{X} \in \mathcal{R}'} \beta_{\mathbf{X}} \mathbf{X}_i + \epsilon_i, \quad (8)$$

where $g(\cdot)$ denotes the link function, β_0 the base coefficient (intercept), and $\beta_{\mathbf{X}}$ the vector of coefficients estimated for the non-baseline categories of each variable \mathbf{X} in \mathcal{R}' . ϵ_i is the error term. Note that $\beta_{\mathbf{X}}$ and \mathbf{X}_i are vectors of dimension $c_{\mathbf{X}} - 1$, where $c_{\mathbf{X}}$ is the number of categories in \mathbf{X} .

To identify the order of relevance of the factors, we calculate the variable importance of each variable in the regression (Equation 8). We use the log-likelihood ratio test utilizing the log-likelihood function $\log \mathcal{L}(\cdot)$ to determine the variable importance (see, e.g., Fuino et al., 2022). We compare two nested models M_{base} and M_{small} with the following equation:

$$\lambda = -2 \cdot \{\log \mathcal{L}(M_{\text{small}}) - \log \mathcal{L}(M_{\text{base}})\}, \quad (9)$$

where M_{base} denotes a reference model with n degrees of freedom, and M_{small} represents an alternative model with $n - m$ degrees of freedom. In our context, the test involves evaluating the log-likelihood ratio using model (8) as the reference model. Thereby, n is the total number of non-baseline categories across all variables in \mathcal{R}' . The analysis then considers M_{small} using the same model but with one term removed ($m = 1$). A larger log-likelihood ratio statistic between both models indicates greater significance for the variable that has been removed, indicating a more substantial contribution to explaining the response variable.

Random forest modeling To confirm the stability and robustness of the variables in \mathcal{R}' , we utilize a second feature selection algorithm based on a random forest. This involves performing recursive feature elimination (RFE) with cross-validation to verify the results obtained from the

logistic regression and variable importance ranking. The strength of the random forest lies in its ability to handle non-linearities and capture intricate patterns, which may pose challenges for more conventional regression models (Ugarte Montero and Wagner, 2023).² Therefore, implementing a random forest model provides an additional verification level, ensuring the outcomes’ consistency. In short, the RFE process can be represented as follows:

$$\text{RFE}(X, y, \text{function, method, repeats, folds}), \quad (10)$$

where X denotes the feature matrix containing all predictor variables in \mathcal{R} , and y stands for the response IIN . The RFE settings include specifying the function to “random forest”, the method to “repeated-cross validation”, repeats to five and folds to ten.

5.4 Results

In the following, we present the results of the regression analysis (Equation 8) and the importance ranking of the factors derived from the log-likelihood test (9). We also provide a robustness check based on the random forest RFE (Equation 10). In a separate section, we further examine specific drivers of SHI by exploring factors related to insurance demand and insurance practice.

5.4.1 Drivers of smart home insurance

In Table 5.4 we display an overview of the logistic regression and random forest modeling results. For each of the nine predictor variables retained in the reduced regression model (8), we display the estimates of the coefficients and their significance. For categorical variables with levels “disagree”, “neutral”, and “agree”, and “dislike”, “neutral”, and “like”, we take the “neutral” option as a baseline to identify the significance of the agreement effects in both directions. The log-likelihood ratio statistic (9) provides a rank and importance level to each variable, reflecting its explanatory power. Moreover, we assess each predictor’s relative contribution in the random forest model (10) and report the variables’ rank and importance. In the last column in Table 5.4, we indicate the models (regression, random forest) where each variable is included.

Regression results and variable importance The stepwise selection algorithm based on the BIC proved instrumental in distilling the 65 variables into a reduced regression model (8), revealing nine significant factors that impact the interest in SHI. The log-likelihood ratio test (9) helped assess the variables’ relative importance. The selected variables highlight the significance of SHI incentives and costs in shaping interest in SHI. The variable for reimbursement of purchase costs shows particularly significant effects and ranks first in the ratio test. It is followed by another variable related to costs, the concern associated with the perception of smart home devices as a non-essential luxury, which also exhibits pronounced significance levels. Additionally, SHI services are closely linked to increased interest in SHI. We find that willingness to share data with insurers and receive proactive advice emerge as highly significant variables, ranked third

²We examine the impact of data set rebalancing on the RFE process. As 41% of our sample is interested in SHI and 59% are not, there is a slight imbalance in the data set that could cause issues in machine learning classification. To evaluate the effects on predictive performance metrics such as accuracy, precision, recall, and F1-score, we employed various rebalancing techniques (down, up, and random over-sampling). Our observations suggest that rebalancing the data set is unnecessary, as no sampling method outperformed all metrics.

Variable	Logistic regression					Random forest		Inclusion in model
	β -estimate	p -value	Sig.	λ -rank	Importance	Rank	Importance	
(Intercept)	-3.243	<0.001	***					
Reimbursement of purchase costs (baseline: neutral)				1	37.58	2	14.59	both
Disagree	0.159	0.548						
Agree	1.105	<0.001	***					
Non-essential luxuries (baseline: neutral)				2	29.70	(11)	(7.13)	regression
Disagree	0.884	<0.001	***					
Agree	-0.118	0.563						
Share data with insurer (baseline: neutral)				3	27.03	1	14.69	both
Disagree	-0.736	<0.001	***					
Agree	0.275	0.190						
Advice from insurer (baseline: neutral)				4	26.03	6	11.73	both
Disagree	0.056	0.849						
Agree	0.938	<0.001	***					
Behavior change (baseline: neutral)				5	25.63	3	14.22	both
Disagree	-0.341	0.208						
Agree	0.705	<0.001	***					
Technology experimenter (baseline: neutral)				6	23.86	7	9.28	both
Disagree	-0.360	0.150						
Agree	0.603	0.003	**					
Discount on insurance premium (baseline: neutral)				7	20.27	4	13.12	both
Disagree	0.334	0.432						
Agree	0.963	<0.001	***					
Health application (baseline: neutral)				8	16.49	8	8.95	both
Dislike	-0.418	0.074	.					
Like	0.395	0.047	*					
Language (baseline: German)				9	16.29	(17)	(3.88)	regression
French	0.709	<0.001	***					
Automatic premium adjustment (baseline: neutral)				n.a.	n.a.	5	12.36	random forest

Notes: The significance levels (column “Sig.”) for the coefficients of the logistic regression are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The RFE recommends the inclusion of eight variables in the final model. Two variables of the regression model only rank 11 and 17. We present their random forest rank and importance level in parentheses (as they are not a part of the final RFE model). The last variable in the table is not included in the logistic regression but ranks 5 in the RFE. “n.a.” stands for not applicable.

Table 5.4: Results from the logistic regression model (8) and random forest model (10).

and fourth, respectively. Variables such as behavior change and discounts on insurance premiums, ranked fifth and seventh, respectively, once again emphasize the crucial impact of costs and incentives on interest. Personality traits received lower rankings, but there are still some significant relationships. Individuals who enjoy experimenting with new technologies (ranked sixth), prefer mobile health devices (ranked eighth), and reside in the French-speaking region of Switzerland (ranked ninth) show more significant interest.

Robustness check based on random forests We use the RFE model (10) to confirm the variable selection by looking at each variable’s relative contribution to the model’s predictive performance, thereby enhancing the robustness of our findings. The results from the RFE confirm the regression model to a large extent. The RFE identifies eight relevant variables, including seven, i.e., excluding two of the nine, from the regression model and introducing one new variable (see Table 5.4). A visual representation of the feature extraction process with information on the trees and the mean minimal depth, an alternative importance metric, is reported in Figures 5.4 and 5.5 in the Appendix. In the variable ranking of the RFE, we observe a prioritization of variables relating to SHI incentives and costs as well as services of a SHI offering rather than personality traits. It upholds four cost-related variables, substituting

the perception of devices as non-essential luxuries with a variable related to the importance of automatic premium adjustments. Furthermore, it maintains two service-related variables and emphasizes the willingness to share data with the insurer.

5.4.2 Additional common factors driving insurance interest

The results of the above regression and random forest applications provide a baseline model for specifically studying additional variables of interest. In this section, we report on the results when adding manually specific variables to the reduced regression model (Equation 8) with the aim of further decoding policyholder profiles within SHI. Two extensions are of particular interest. Firstly, we consider the factors identified in Section 5.2.1 that typically contribute to insurance demand. These factors primarily relate to income, age, gender, education, risk aversion, and household characteristics. If the traits are not directly available in our data, we use variables, where available, that serve as proxies for the mentioned characteristics. Secondly, we test factors that insurance practitioners use to determine household insurance premiums. Based on (Wagner and Fuino, 2024, Chap. 6), we incorporated variables on household size, home ownership, and insurance app usage.

Table 5.5 presents an overview of both proposed model extensions taken separately. We report on the additional variables’ significance and examine the extended model’s explanatory power and accuracy. The full details of the two model extensions, including the regression coefficients and p -values for each category of the variable, are reported in Tables 5.6 and 5.7 in the Appendix.

Model	Description and additional variables	Sig.	BIC value	Pseudo- R^2	Accuracy
Reduced model (8)	See Table 5.4, without additional variables.		1 103.5	0.355	0.774
Insurance Demand	Extension with insurance demand variables.		1 180.3	0.360	0.774
	Income sufficiency (baseline: with great difficulty)	No			
	Age (baseline: 45–64)	No			
	Gender (baseline: female)	No			
	Education (baseline: high school)	No			
	Risk-taking level (baseline: neutral)	No			
Insurance Practice	Household with kid(s) (baseline: no)	No			
	Extension with insurance practice variables.		1 128.6	0.357	0.774
	Single household (baseline: no)	No			
	Household with kid(s) (baseline: no)	No			
	Home ownership (baseline: rent)	No			
	Insurance app in use (baseline: no)	No			

Note: In the “Sig.” column, “No” indicates that none of the categories of the predictor variable reach a significance level of at least 10%.

Table 5.5: Overview of the results of the regression model extensions for insurance demand and insurance practice variables.

Overall, we observe that none of the additional variables are significantly connected to SHI interest. Moreover, the significance levels of the original reduced regression model remain constant even when the model is extended (see the Appendix). This confirms the relevance of the identified variables in the reduced regression model and the robustness of the applied methodology. In regards to the model’s explanatory power, we demonstrate that a slight increase in the pseudo- R^2 value is observed.³ This increase comes with an increase in the BIC value, indi-

³Pseudo- R^2 is a measure of the goodness of fit of the logistic regression model, indicating the proportion of

cating reduced model parsimony, which has a more significant impact than the increase in the pseudo- R^2 . The accuracy levels remain constant, indicating that the extended models do not improve the predictive performance.⁴

5.5 Discussion

When considering SHI from the perspective of the fundamental function of insurance, new dynamics emerge. Insurance involves exchanging an uncertain loss of unknown magnitude for a small loss, the premium (Zweifel and Eisen, 2012, adapted from Hax, 1964). With SHI, insurers can integrate an additional flow of information from IoT data collected by the insured to improve estimation, control, and proactive reduction of losses. However, this exchange may also create new expectations from policyholders beyond traditional financial compensation.


In our work, we identify early trends in these new policyholder expectations. Firstly, individuals expect to share the insurer’s improved loss experience. Therefore, they anticipate compensation for adopting new technology and changing their behavior. The results indicate a strong relationship between interest in SHI and financial incentives, such as the reimbursement of purchase costs and discounts on premiums. However, insurers are cautiously evaluating business cases, as the impact on loss distributions has not yet been proven. Market activity, as outlined in Section 5.2.3, suggests that insurers are testing solutions in lines with high premiums and high losses, such as water damage. Secondly, individuals express concerns regarding the costs of IoT offerings and issues related to dependence and privacy (McFall and Moor, 2018). Therefore, insurance companies offering SHI must convince their customers that it is not just a gimmick. This is further supported by the observation that interest decreases when SHI is perceived as an unnecessary luxury. Thirdly, insurers should adopt a more service-oriented approach beyond the traditional premium-payment model since proactive advice from insurers is positively associated with interest in SHI. Fourthly, we observe that traditional demographic factors, such as income and age, are not linked to interest and, potentially, demand for SHI. Instead, variables such as technological capabilities, willingness to share data, and preferences for specific services emerge as characteristics of SHI adopters. Figure 5.1 summarizes the new expectations and shows that the findings validate the proposed hypotheses. As we group the variables into their respective research focus along the insurance demand respectively technology adoption literature, we observe that the determinants of insurance demand (H1, as introduced in Section 5.2.1) as well as the drivers of IoT technology adoption (H2, as introduced in Section 5.2.2) currently influence SHI. The evidence further provides insights into the nuanced interplay between these two fields.

Research on interest in and demand for SHI is still in its early stages. This is reflected in the comparatively lower explanatory power of the identified factors (see Table 5.5, Section 5.4.2), when compared to studies from the two neighboring areas of insurance demand (Park and Lemaire, 2012; Trinh et al., 2020) and smart home technology adoption (Baudier et al., 2020; Große-Kreul, 2022). Future investigations will provide more certainty about the

variance explained. The term “pseudo” is used because it adapts the concept from linear regression to logistic regression. Higher values of pseudo- R^2 indicate a better fit. However, it is important to note that the pseudo- R^2 in logistic regression does not exactly correspond to the adjusted R^2 in linear regression (Walker and Smith, 2016).

⁴Accuracy measures the correctness of predictions and reflects the proportion of correctly identified instances among the total. This metric was chosen for comparison because it is central to the RFE process applied previously.

	TECHNOLOGY ADOPTION	NEW EXPECTATIONS	INSURANCE DEMAND
Value proposition	Services	Services Loss indemnity	Loss indemnity
Economic drivers	Price of IoT <i>NS: Income</i>	Reimbursement of IoT purchase costs Premium discounts on insurance	Price of insurance <i>NS: Income</i>
Demographic drivers	<i>NS: Age, Gender, Home ownership</i>	Residency location	<i>NS: Age, Gender, Household size</i>
Social and cultural drivers	Technology affinity	Technology affinity Health application	<i>NS: Risk aversion, Education</i>
Structural drivers	Support services from provider	Services from provider	
Concerns and risks	Privacy <i>NS: Cybersecurity</i>	Willingness to share data Technology as non-essential luxuries	Financial risks



SMART HOME INSURANCE ADOPTION INTENTION
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Note: The abbreviation “NS” stands for “not significant.” It is used to indicate factors that only apply to technology adoption or insurance demand but are not significant for the intention to adopt SHI.

Figure 5.1: Summary of the factors driving the adoption of smart home insurance, building on the insurance demand categories proposed by Outreville (2013) and extended by concerns and risks.

drivers. Other IoT insurance applications, such as telematics (Milanović et al., 2020; Mortimer et al., 2018; Tian et al., 2020) and wearables (Soliño-Fernandez et al., 2019), show that moderating and mediating relationships exist and that the driving forces will become more apparent as the value proposition of IoT insurance becomes clearer. At this stage, insurers may already need to reposition themselves. To align with the value proposition that prospective consumers expect, insurers should base their offerings on insurance loss indemnity and proactive (risk management) advisory services.

5.6 Conclusion

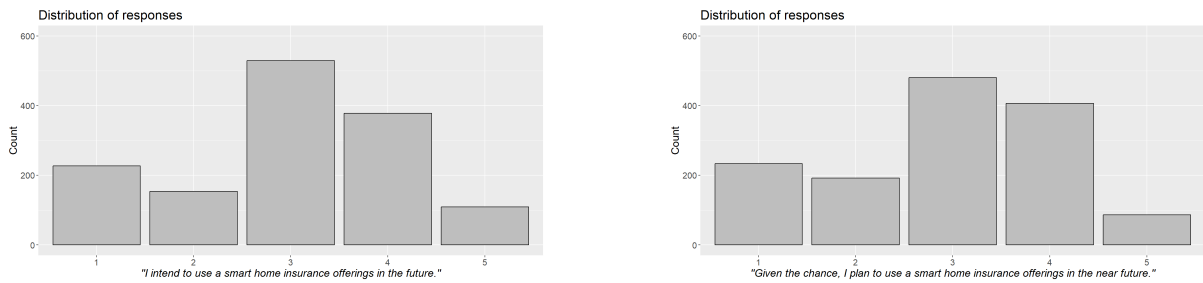
This study aimed to examine the factors influencing an individual’s interest in smart home insurance (SHI) offerings and identify potential drivers. The results highlight the importance of SHI costs, specifically the role of incentives in increasing interest. Additionally, we found that insurers’ provision of suitable SHI services and willingness to share data with insurers are other crucial factors that affect interest in SHI. From a vast set of personality traits, only factors related to higher technology affinity and residency in the French-speaking language region of Switzerland can be used to depict a more nuanced picture of an interested individual. Based on these observations, we demonstrate how IoT-enabled insurance can enhance the policyholder-insurance relationship. The insured not only pays a fixed premium but also provides data. In exchange, they expect a discount on the purchase of technology, incentives for risk prevention behavior, and loss indemnity in case of a defined event. From an insurance perspective, the core benefit of SHI results from the reduced uncertainty regarding future losses related to one’s home. To fully realize this potential, however, the parties must align on the expected benefits

and efforts of their risk management activities – and share the costs of those activities.

While this study contributes to understanding the factors determining SHI adoption, its scope, and generalizability are limited by inherent constraints. The data is self-reported, lacks a temporal dimension, and has a geographic focus. Additionally, insurance demand variables are approximated, and potential biases may arise related to the topic's complexity and the participants' demographic distribution. Future research in the field should focus on addressing the identified weaknesses of the data set. Another area of interest is examining the utility of SHI using traditional insurance models. Such activities include discrete choice experiments that target and model the identified features of SHI policy to varying degrees. In addition, our findings can also be validated in other insurance markets of interest. Given the high household and liability saturation in the Swiss market, it may be possible that considerations differ from those in markets where SHI is not a substitute for existing insurance. Finally, analyzing the portfolios of active SHI providers has great potential, particularly in validating their prevention potential in reducing claims costs.

5.7 Appendix

Distribution of the responses concerning the interest in a SHI offering



(a): Distribution of responses in the statement “*I intend to use a smart home insurance offerings in the future.*”

(b): Distribution of responses in the statement “*Given the chance, I plan to use a smart home insurance offerings in the near future.*”

Note: The five levels 1 to 5 in the graphs correspond to the five levels of the Likert scale (“strongly disagree” to “strongly agree”).

Figure 5.2: Distribution of the responses concerning the interest in a SHI offering ($N = 1\,397$).

Heatmap of the responses concerning the interest in a SHI offering

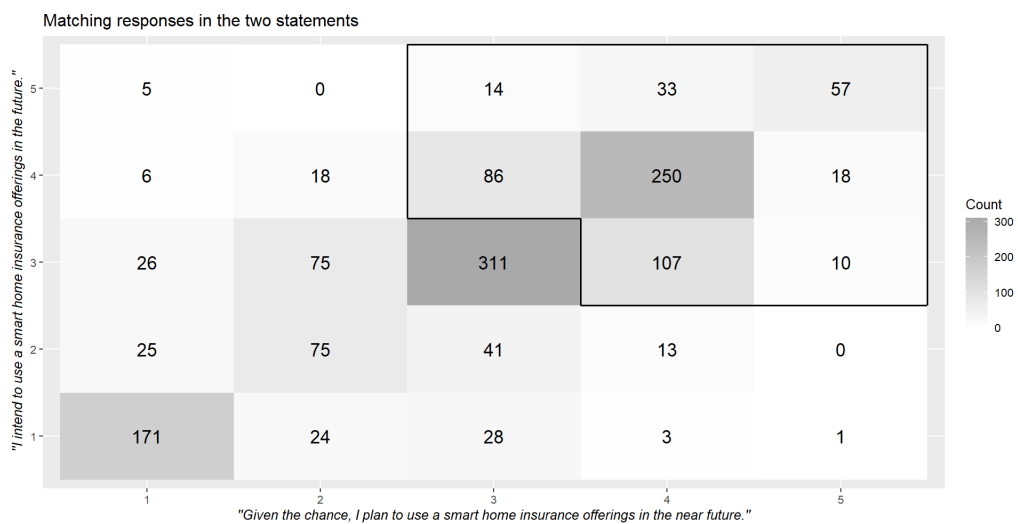
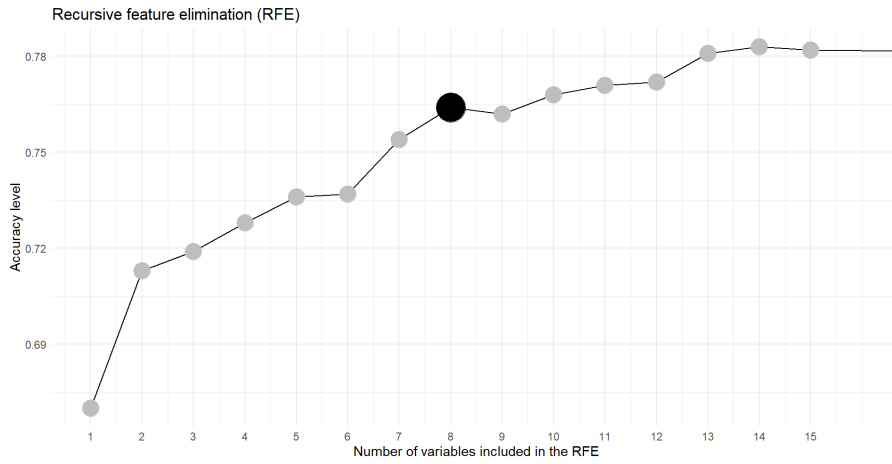


Figure 5.3: Heatmap of the responses concerning the interest in a SHI offering ($N = 1\,397$).

Illustration of the random forest recursive feature elimination process



Note: Although the inclusion of more than eight variables results in a slight improvement in accuracy, we limit the complexity of the model to eight features in order to prioritize simplicity, ease of interpretation, and improved generalization to new data. This choice favors a more parsimonious model without compromising performance.

Figure 5.4: Illustration of the random forest recursive feature elimination process (10).

Variable importance from the random forest mean minimal depth distribution

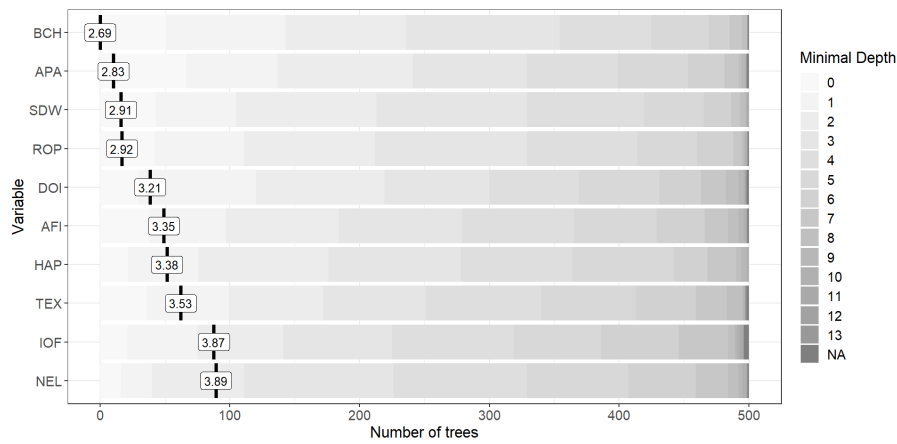


Figure 5.5: Variable importance from the random forest mean minimal depth distribution.

Results of the extended regression models (presented in Section 5.4.2)

Variable	β -estimate	p -value	Sig.
(Intercept)	-3.301	<0.001	***
Share data with insurer (baseline: neutral)			
Disagree	-0.777	<0.001	***
Agree	0.248	0.246	
Behavior change (baseline: neutral)			
Disagree	-0.324	0.235	
Agree	0.729	<0.001	***
Technology experimenter (baseline: neutral)			
Disagree	-0.358	0.170	
Agree	0.588	0.005	**
Reimbursement of purchase costs (baseline: neutral)			
Disagree	0.162	0.542	
Agree	1.126	<0.001	***
Advice from insurer (baseline: neutral)			
Disagree	0.080	0.790	
Agree	0.947	<0.001	***
Non-essential luxuries (baseline: neutral)			
Disagree	0.878	<0.001	***
Agree	-0.122	0.553	
Language (baseline: German)			
French	0.719	<0.001	***
Discount on insurance premium (baseline: neutral)			
Disagree	0.287	0.505	
Agree	0.935	<0.001	***
Health application (baseline: neutral)			
Disagree	-0.445	0.061	.
Agree	0.418	0.038	*
Income sufficiency (baseline: with great difficulty)			
With some difficulty	0.356	0.373	
Fairly easily	0.118	0.764	
Easily	0.160	0.706	
Age (baseline: 45–54)			
55–64	-0.337	0.118	
65–74	-0.366	0.108	
75+ years	-0.272	0.403	
Gender (baseline: female)			
Male	0.177	0.293	
Education (baseline: high school)			
Mandatory school	0.036	0.942	
Higher education	-0.050	0.787	
Risk-taking level (baseline: neutral)			
Not willing	0.183	0.412	
Willing	0.052	0.783	
Household with kid(s) (baseline: no)			
Yes	-0.051	0.810	

Note: The significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.6: Results of the extended regression model based on insurance demand.

Variable	β -estimate	p -value	Sig.
(Intercept)	-3.398	<0.001	***
Share data with insurer (baseline: neutral)			
Disagree	-0.736	<0.001	***
Agree	0.262	0.214	
Behavior change (baseline: neutral)			
Disagree	-0.378	0.165	
Agree	0.686	<0.001	***
Technology experimenter (baseline: neutral)			
Disagree	-0.322	0.200	
Agree	0.612	0.003	**
Reimbursement of purchase costs (baseline: neutral)			
Disagree	0.158	0.553	
Agree	1.117	<0.001	***
Advice from insurer (baseline: neutral)			
Disagree	0.057	0.847	
Agree	0.950	<0.001	***
Non-essential luxuries (baseline: neutral)			
Disagree	0.853	<0.001	***
Agree	-0.128	0.532	
Language (baseline: German)			
French	0.713	<0.001	***
Discount on insurance premium (baseline: neutral)			
Disagree	0.353	0.407	
Agree	0.946	<0.001	***
Health application (baseline: neutral)			
Disagree	-0.425	0.071	.
Agree	0.363	0.070	.
Single household (baseline: no)			
Yes	0.195	0.323	
Household with kid(s) (baseline: no)			
Yes	0.156	0.447	
Home ownership (baseline: rent)			
Own	-0.011	0.947	
Insurance app in use (baseline: no)			
Yes	0.210	0.203	

Note: The significance levels are: . $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.7: Results of the extended regression model based on insurance practice.

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