Home alone: The role of Personality and Beliefs in acceptance of remote health monitoring utilizing artificial intelligence in elderly care.

Samuel Stahl
Department of Behavioral Management and Social sciences, University of Twente
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1st Supervisor: Dr. L.M.A. Braakman-Jansen,
2nd Supervisor: Dr. J.E. Spook

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Abstract

Background: The rising global aging population necessitates effective healthcare solutions. Aging in place, enabled by remote health monitoring (RHM) technologies like AI-based Radio Frequency (RF) sensing, presents a promising strategy due to their effectiveness and unobtrusiveness. Despite potential advantages, like reducing health care costs, user acceptance for these technologies remains limited.

Aim: This study explores how personality traits and beliefs influence the acceptance of AI-based RHM in elderly care among Germans in order to gain knowledge about problems and solutions to improve acceptance rates.

Methods: Using an online questionnaire, this quantitative study collected data from German residents aged 45 and above. Participants were invited by convenience sampling method utilizing the snowball sampling. Participants' personality traits were measured with the Ten Item Personality Scale (TIPI). Beliefs and acceptance of AI-RHM was evaluated based on the acceptance model of Jaschinski et al (2021). In the analysis descriptive statistics and spearman's rank correlations were calculated.

Results: The sample consisted of 57 Participants with a mean age 56.26 (SD = 6.09) and more female (63.2%) than male (36.8%). Participants have shown to neither reject nor accept AI-RHM with an acceptance score of 2.95 (SD = 0.88). All beliefs of the acceptance model of Jaschinski et al. (2021) showed a significant effect, while two beliefs "Loss of human touch" (r = -0.22, p = n.s.) and "Loss of privacy" (r = -0.21, p = n.s.) showed a negative non-significant effect on acceptance. A significant positive correlation was found between acceptance and openness (r = 0.34, p < .01).

Conclusion: The study highlighted that Attitude, as one of the most influential factors, significantly influenced acceptance levels. Additionally, the study revealed that openness was positively associated with acceptance, suggesting that individuals who are more open to experiences are more likely to accept AI-RHM. These findings have implications for interventions aiming to enhance acceptance and adoption rates and underscore the importance of comprehensive acceptance models that consider regional differences.

Keywords: Acceptance, Artificial Intelligence, Remote Health Monitoring, Personality Traits

Introduction

Most countries are experiencing a significant demographic shift, with an increasing number of older adults due to longer life expectancies and declining birth rates. By 2050, the global population aged 65 and older is expected to double from 761 million in 2021 to 1.6 billion (United Nations, 2023). The growing aging population presents numerous challenges, including an increased prevalence of chronic diseases, like diabetes, and the need for professional caregivers (United Nations, 2023). In Germany the ratio between nursing staff and people in care changed from 2009 with a ratio of 1:2.6 to 1:3.4 in 2019 (Satistisches Bundesamt, n.d.). Consequently, there is an urgent need to reorganize healthcare services to better address the needs of this population (World Health Organisation, 2022).

One potential solution to these challenges is the promotion of aging in place. Aging in place allows older adults to maintain their independence and continue living in their own homes and communities (Iecovich, 2014). This is especially important since most elderly individuals aspire to maintain their independence and reside in their homes for the longest possible duration (Vergouw et al., 2020). In addition, the goal of aging in place is to maintain older adults' sense of identity, personhood, and connection to their environment, while also providing appropriate support and services to promote safety, independence, and well-being (Iecovich, 2014).

E-health technologies can support aging in place. This can be achieved through monitoring of elderly's´ health status and early detection of potential health risks (Kim et al., 2017). According to the World Health Organization (n.d.), e-health is defined as the cost-effective and secure use of information and communication technologies (ICT) in support of health and health-related fields. It encompasses a broad range of interventions including telehealth, remote health monitoring (RHM), telemedicine, mobile health (mHealth), electronic medical or health records (eMR/eHR), big data, wearables, and even artificial intelligence.

Current scholarly texts often refer to the concept of RHM using similar terms. These include "remote patient monitoring" (Giger et al., 2015; Taiwo & Ezugwu, 2020), "in-home health monitoring" (Philip et al., 2021), or as part of larger ideas like "ambient assisted living" (AAL; Jaschinski et al., 2021) and "home telehealth services" (Cimpeman et al., 2013), albeit with minor differences in the definitions used. For this paper following definition is used: Remote patient or health monitoring is the process of collecting, transmitting, analyzing, and communicating a patient's health data from home to healthcare providers using health technologies like implanted monitors, wearable sensors, wireless devices, and mobile apps. It facilitates continuous health monitoring, chronic disease management, and personalized medicine, either in real-time or at a delay, using advanced technologies such as artificial intelligence and machine learning (American Telemedicine Association, 2020). According to Sharma et al. (2021) remote health monitoring technologies can be grouped into three primary categories: “wearable sensing systems (e.g., smartwatches, smart clothing, and mobile phones), vision-based systems (e.g., surveillance cameras and Kinect), and radio frequency (RF)-based sensing systems (e.g., Wi-Fi, radar, and wireless sensors integrated into everyday objects)”. These sensors can gather vital sign data such as human activity with heart rate and breathing rate. (Sharma et al.,2021). RF-based sensing systems are especially well-suited for elderly care due to their unobtrusive nature, as they require no direct contact with the user and function effectively in non-line-of-sight areas. Unobtrusive sensing systems are promising for older adults with cognitive impairment such as dementia, as they can detect cognitive impairments and seizures in a timely manner, preventing damage and reducing the risk of injury (Sharma et al., 2021). Thus, in this study a not completely developed unobtrusive system using RF based sensing technology will be evaluated.

AI Remote Health Monitoring (AI-RHM) combines sensing technology such as RF based sensing technology with artificial intelligence. Artificial intelligence (AI) strives to emulate human cognitive abilities (Jiang et al., 2017). AI systems in healthcare use machine learning algorithms, a subset of AI that allows computers to learn from and make predictions based on data, and predictive analytics to analyze vast amounts of information from sources such as electronic health records, wearable devices, and sensors. These systems aid in decision-making, including diagnosis, treatment planning, and patient monitoring (Jiang et al., 2017). As AI systems receive increasingly personalized data from individuals, they continually refine their predictive capabilities by adapting to the distinct behaviors and patterns of the elderly population (Esteva et al., 2019). Thus, artificial intelligence incorporates sensing technologies to monitor health conditions, offer assistance, and notify caregivers or healthcare professionals when needed (Cicibas & Yildirim, 2019; Doyle et al., 2015). In this way one could say artificial intelligence works like a brain receiving and analyzing sensory input as a result giving recommendations and taking actions like notifying caregivers.

Despite the advancements in the technology and potential advantages, the widespread acceptance (intention to use a technology) of remote health monitoring systems have not yet reached the anticipated levels (Walker et al., 2019; Jaschinski, 2014). Despite Germany's reputation for healthcare excellence, its acceptance and adoption of digital health and smart health innovations has been somewhat languid, not fully harnessing its potential (Girvan, 2020). It is known that one of the primary concerns hindering acceptance and adoption of AI-based monitoring systems is the perceived problem of security and data protection. Park and Jang (2022) highlighted worries about hacking, data breaches, and the criminal exploitation of confidential data, which can lead users to reevaluate the practical utility of such AI systems. Sharma et al. (2021), however, posited that the adoption of unobtrusive systems could potentially mitigate some of these concerns. These systems gather and preserve data in its raw format, accounting for users ‘privacy in specific settings (e.g., bathrooms).

One area that has not been thoroughly investigated in the context of acceptance towards AI-based monitoring system is the influence of individual personality traits. This knowledge has the potential to offer valuable insights into user characteristics, which could be helpful in addressing the challenge of low acceptance rates. The Five Factor Model (FFM) of personality, commonly known as the Big Five personality traits, comprises extroversion, agreeableness, conscientiousness, neuroticism, and openness (McCrae & John, 1992). These traits can be measured with an easy questionnaire the Ten Item Personality Scale (TIPI).

Brown and Taylor (2014) posited a connection between the Big Five personality dimensions and the adoption of novel technologies. Özbek et al., (2014) argue that extraverts and people higher in openness have higher scores in accepting new technology. According to them, extraverts tend to adopt innovations to enhance their social status, while individuals who are open to change willingly embrace new experiences. A recent study by Huo et al. (2022) suggests that the personality traits of extraversion and neuroticism often have a positive relationship with the acceptance of new technologies, which could potentially include AI. However, the same study also noted instances of a negative relationship between acceptance outcomes and these traits (Huo et al., 2022). On the other hand, neuroticism is a personality trait marked by the tendency to experience negative emotions, such as anxiety, depression, and vulnerability. Individuals with high neuroticism (low emotional stability) levels might perceive AI-based health monitoring systems as less appealing due to their heightened sensitivity to stressors and a greater sense of vulnerability. This could potentially impact their intention to use AI-based health monitoring systems (Devaraj, Easley, & Crant, 2008). Conscientiousness, a personality trait linked to organized, responsible, and dependable individuals, may positively influence the acceptance of AI-based health monitoring systems (Svendsen et al., 2013). People with high conscientiousness levels are likely to adopt such systems because of their strong sense of responsibility and commitment to adhering to routines and schedules (Svendsen et al., 2013). This dedication may result in a higher intention to use AI-based health monitoring systems.

This study aims to bridge this research gap by exploring how personality affects the acceptance of AI-RHM. This could help gain knowledge for intervention designs to better target people, thus improving effectiveness and efficiency of interventions.

One model that can account for the acceptance and beliefs of remote health monitoring is the acceptance model of ambient assisted living developed by Jaschinski et al. (2021) (Appendix E). It considers 15 factors specifically relevant for this more sophisticated technology in healthcare context such as social norm, personal norm, safe and independent living, relief of family burden, loss of privacy etc., while demonstrating its potential to effectively assess the acceptance of AI-RHM in healthcare settings. Each factor, referred to as latent factor/variable, was at least measured with 3 items. The foundation of the model was the theory of planned behavior (TPB) and adjusted to the specific context and needs for ambient assisted living. The Theory of Planned Behavior (TPB) was chosen for three key reasons: it offers insights into early user acceptance by emphasizing attitudes, social factors, and norms; it provides valuable input for the design of new technologies beyond just assessing usefulness and ease of use; and it allows for the inclusion of additional variables, making it an ideal basis for developing a new model for technology acceptance (Jaschinski et al., 2021).

Based on the findings from the extant literature and research aims to fill the research gap the following research questions can be proposed regarding the influence of personality traits on the acceptance of AI-based monitoring systems for elderly care within the Jaschinski acceptance model:

RQ 1: “What is the level of user acceptance towards AI-RHM in the context of elderly care among Germans.”

RQ2: “To what extent are the beliefs from the Jaschinski acceptance model (Attitude toward using AI-RHM, Social norm, Personal norm, Perceived behavioral control, Safe and independent living, Relief of family burden, Loss of privacy, Loss of human touch, Caregiver influence, Personal innovativeness, Self-efficacy, Financial cost) associated with user acceptance towards AI-RHM among Germans.

RQ 3: “To what extent are personality traits (openness, extraversion, emotional stability (opposite of neuroticism), conscientiousness, and agreeableness) associated with user acceptance towards AI-RHM among Germans."

Method

Study Design

The study is a quantitative study based on an online questionnaire survey design. For this study, a cross-sectional design was chosen to investigate the research questions.

Participants

For this study, participants were required to meet the inclusion criteria of being 45 years of age or older living alone or with a partner. This age criteria were set to examine the acceptance and beliefs of future generation towards AI-RHM and still have current participants from the current elderly population. Additionally, participants were required to reside in Germany, a criterion that was ensured through the sampling method. As the last inclusion criteria to mention, participants needed a smartphone, tablet, laptop, or computer with a working internet connection. In addition, participants needed an e-mail account. To recruit participants for the study, a convenient sampling method utilizing the snowball sampling approach was chosen. The researcher initially provided the questionnaire to 150 relatives or friends meeting the inclusion criteria. These individuals were requested to further share the questionnaire with three other relatives or friends who meet the inclusion criteria for the study.

Materials and Measures

The questionnaire showed participants the technology in text-based and picture-based form (Figure 1). This was used as an introduction to the workings and benefits of AI-RHM. In addition, the questionnaire informed the researchers with background information (age, gender), pre-existing use of health technology e.g., smartwatches, whether they are receiving home care and living alone or with a partner (Appendix C), data of the TIPI (Appendix E), and with data from the conceptual model of Jaschinski et al. (2021) (Appendix F).

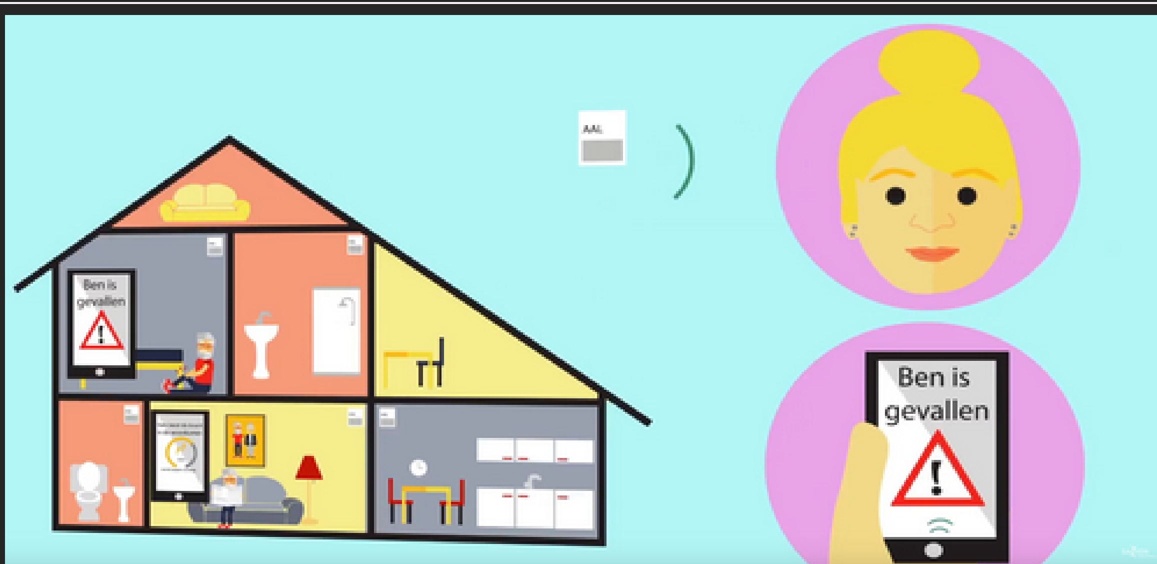
Figure 1

Introduction to What is AI based health-monitoring (AI-RHM)

AI-based health monitoring is an innovative technology that utilizes artificial intelligence (AI) to track and analyze various aspects of an individual's health. AI is a type of technology that uses machine learning to learn from patterns and data collected and mimic human decision making. With AI-RHM, a discreet sensor is placed in each room to detect and localize movement, daily activities, personal presence, speed/velocity of movement, and breathing. The sensors use existing Wi-Fi waves, which are already present in your home, to collect this data.

When a person moves, the sensor detects the disruption in the Wi-Fi waves, and the data collected is fed into the AI. The AI then compares the collected data to the individual's baseline health information and can determine if there is a deviation from the norm. If needed, the system can alert designated family members or caregivers to provide prompt assistance and timely intervention. For individuals with dementia who may struggle with remembering medication intake or exhibit unusual behavior, such as leaving the house for an extended period, the system can alert caregivers or family members to provide timely care and support.

Overall, AI-based health monitoring can improve the quality of life for older adults, with or without health conditions, by reducing hospital visits and providing timely support in case of emergencies or medication management. The system is non-intrusive and does not require any wearables. The installation cost is around 10,000 Euro. By utilizing this technology, older adults can maintain their independence while ensuring that their health and safety are being monitored.



In the picture you can see a sensor in each room and the potential to notify a family member or carer in an emergency.

Note. Picture was based on the study of Jaschinski et al. (2021), material was post tested and participants had a vivid idea about AI-RHM

Acceptance

The second primary section of the survey was designed based on AAL's conceptual framework (Jaschinski et al., 2021), which evaluates the acceptance and adoption of AAL, and then tailored to the context of AI-RHM. AAL utilizes technology and intelligent systems to build a living space that fosters support for older adults or individuals with disabilities, which closely aligns with the goals of AI-RHM. To gauge the acceptance of AI-RHM, the phrasing of the technology in the questionnaire was altered. The model was measured with a 5-point Likert scale (1 = strongly disagree, 5 = strongly agree). The final measurement acceptance model by the Jaschinski et al. (2021) comprised of 15 latent variables and 63 items. All latent variables can be seen in Table 1. Acceptance was measured based on the items of Intention to use AI-RHM. In the original study the model's fit measures were acceptable to good: comparative fit index (CFI) = .93, root mean square error of approximation (RMSEA) = .04, Tucker Lewis Index (TLI)=.92 and standardized root mean square (SRMR) = .05. The Cronbach's alpha values for the constructs demonstrate high internal consistency. For example, in the original study of Jaschinski et al. (2021) the construct "Intention to Use AAL" had a Cronbach's alpha of .94, and the "Attitude Toward Using AAL" construct had an alpha of .93. While the lowest Cronbach´s alpha values were .77 and .81 for “Personal Norm” and “Social Norm”, respectively. For this study, two latent variables were deleted from the questionnaire, “human touch norm”, and “Reliability” because of non-significant effects in the original study.

Table 1

Conceptual acceptance Model of Jaschinski et al. (2021)

Latent Variable	**Number of items in the survey**	**Example item**	**Cronbach´s alpha α**
Acceptance (Intention to use AI-RHM) (ACC)	4	In the future, I intend to use AI-RHM.	.94
Attitude toward using AI-RHM (ATT)	6	I (like/dislike) the idea of using AI-RHM.	.93

Social norm (SN)	3	Most people whose opinion I value, would think positively about my use of AI-RHM.	.81
Personal norm (PN)	3	I view myself as a user of technology for my health and well-being.	.77
Perceived behavioral control (PBC)	4	I would be able to use AI-RHM technology.	.82
Safe and independent living (SIL)	7	If I use AI-RHM, I will feel safer in my home.	.88
Relief of family burden (RFB)	4	My use of AI-RHM will give my family members peace of mind.	.85
Loss of privacy (LP)	6	If I use AI-RHM, I worry that my personal information might be shared with others without my permission.	.93
Loss of human touch (LHT)	4	If I use AI-RHM, I will get less personal attention.	.87
Caregiver influence (CI)	3	My caregivers would have a positive view on my use of AAL technology.	.82
Human touch norm (HTN)	4	I prefer personal care over care via AI-RHM.	.87
Personal innovativeness (PI)	4	If I heard about a new information technology, I would look for ways to experiment with it.	.84
Self-efficacy (SE)	5	I feel confident about using AI-RHM.	.82
Reliability (R)	3	I think that AI-RHM is reliable.	.84
Financial cost (FC)	3	I think that using AI-RHM will be expensive.	.86

Personality

Regarding the measurement of personality, the Ten Item Personality Scale (TIPI) was used and consists of 10 questions. It was translated by researchers already into German (Appendix E). The TIPI is measured with a 7-point Likert scale (1 = Strongly disagree – 7 = strongly agree). Each of the five personality traits consisted of two items. The Cronbach alphas in the original study for the Extraversion, Agreeableness, Conscientiousness, Openness to Experience scales were .68, .40, .50, and .45 respectively, while for the Emotional Stability scale, it was .73. The average convergent correlations (r = .77) were significantly higher than the absolute average discriminant correlations (r = .20), and there were no discriminant correlations greater than .36 (Gosling et al., 2003). This indicates a high degree of correlation with measures that the questionnaire is theoretically expected to correlate with. The Cronbach's α coefficients of the German translated version for internal consistency were found to be similar to those of the original version of the TIPI (Muck et al., 2007).

Procedure

To begin the study, the researchers obtained ethical approval from the University of Twente ethics committee (request number: 230514). Once approval was granted, participants were recruited via email. Outlook.com was used to send e-mails to the initial participants. The E-mail sent to friends and relatives of the researcher, provided the participants with the link for the survey measured with Qualtrics, an approximation that the completion of the survey will take 15 minutes, and instructions to further spread the E-mail to friends and relatives living in Germany. The study had a set end date, mentioned in the E-mail, to ensure that data collection remained in line with the approved ethical guidelines.

With access to the Qualtrics survey, software for gathering data from the participants (Qualtrics.com), participants were introduced to AI-RHM as technology (Figure 1). Additionally, participants were informed of the purpose of the research, and the processing of the data (Appendix A). Participants were then presented with the informed consent form, which explained their rights as participants, including the right to withdraw from the study at any time without negative consequences (Appendix B). Following the collection of demographic information, including age, gender, and nationality (Appendix C), participants were instructed to proceed to the questionnaires of interest. They were given clear instructions about the task and were encouraged to provide truthful responses (Appendix D). The first set of questionnaires administered were the TIPI personality questionnaire (Appendix E) and the adopted conceptual model of ambient assistant living acceptance (Appendix F), which aimed to gauge their acceptance and adoption of AI-based health monitoring technology. To ensure language barriers were minimized, the questionnaires were made available in German language, thereby avoiding any confusion or misunderstandings.

Data Analysis

The data collected from the survey was first exported from Qualtrics into an Excel spreadsheet, where it was cleaned by removing unrelated variables, such as IP addresses. The dataset was then restructured from wide to long format. Then negative items were reversed, and the variables were calculated by adding the items and dividing it by the number of items. Thus, extraversion, openness, emotional stability and the variables from the Jaschinski et al. (2021) model were calculated for each participant. To analyze, restructure, and clean the data, the R-studio (2023.03.1+446) software was used, with the following packages: "readxl", “Hmisc”, “corrplot”, "dplyr", "ggplot2", "knitr", "tidyr", "tidyverse", "WriteXLS", and “moments”.

Next, to gain an insight into the sample and answer the first research question, descriptive statistics were calculated for acceptance scores, all relevant variables, and socio demographics, including the mean, median, standard deviation, frequency, and percentage. Afterwards a univariate regression analysis was performed to answer the second research question. For this a spearman correlation between the beliefs of the acceptance model of Jaschinski et al. (2021) and acceptance will be performed. In order to answer the third research question another univariate analysis will be calculated. For this the spearman correlation between the five personality traits and acceptance will be examined. For both correlation analysis a p-value cutoff point of .05 will be set. The distribution of the variables was assessed by plotting histograms and checking for normality using the Shapiro-Wilk test, with a p-value cutoff of .05 to determine whether parametric or non-parametric tests should be used.

Results

The study enrolled a total of 81 participants which had to be reduced to 57 participants due to incomplete answers, all Germans aged above 45 years. The participants had an average age of 56.26 (SD = 6.09). The gender distribution was skewed toward females, with 36 female participants (63.2%) compared to 21 male participants (36.8%). Most of the participants were living with a partner or family (78.9%). The vast majority were not receiving home care (98.2%), with only a single participant (1.8%) in the sample receiving such care. Experience with health technology was relatively rare, with only 9 individuals (15.9%) having experience with a smartwatch and a single participant (1.8%) each for heart rate and pressure monitor (Table 2).

Regarding personality traits, the sample demonstrated high levels of openness (*M* = 5.40, *SD* = 0.89), extraversion (*M* = 4.95, *SD* = 1.18), agreeableness (*M* = 5.36, *SD* = 0.87), conscientiousness (*M* = 5.72, *SD* = 0.89), and emotional stability (*M* = 5.48, *SD* = 0.92) (Table 2).

Regarding acceptance (ACC) towards remote health monitoring utilizing artificial intelligence, the average score in the sample was 2.95 (*SD* = 0.88) (Table 2). This means that participants neither rejected nor accepted AI-RHM.

Table 2

Descriptive Statistics of all variables from the Dataset, N = 57

	Median	M	SD	N	%
Age in years		56.26	6.09		
Gender					
Male				21	36.8
Female				36	63.2
Living Situation					
Living alone				12	21.1
Living with a partner or family				45	78.9
Receiving Home care					
Yes				1	1.8
No				56	98.2
Experience					
Smartwatch				9	15.9
Heart rate monitor				1	1.8
Heart pressure monitor				1	1.8
ACC	3.00	2.95	0.88		
Openness	5.50	5.40	0.89		
Extraversion	5.00	4.95	1.18		
Agreeableness	5.50	5.36	0.87		
Conscientiousness	6.00	5.72	0.89		
Emotional Stability	5.50	5.48	0.92		
ATT	3.67	3.45	0.68		
SN	3.33	3.30	0.72		

PN	3.33	3.27	0.91
PBC	3.50	3.45	0.77
SIL	3.71	3.67	0.62
RFB	4.00	3.82	0.63
LP	3.33	3.30	0.85
LHT	3.00	2.89	0.84
CI	3.67	3.54	0.60
PI	2.75	2.92	1.05
SE	3.60	3.54	0.69
FC	3.00	3.19	0.81

Note. The abbreviations used in this table stand for the following constructs: M = Mean, SE = Standard Error, SD = Standard Deviation, ACC = Acceptance, ATT = Attitude toward using AI-RHM, SN = Social norm, PN = Personal norm, PBC = Perceived behavioral control, SIL = Safe and independent living, RFB = Relief of family burden, LP = Loss of privacy, LHT = Loss of human touch, CI = Caregiver influence, PI = Personal innovativeness, SE = Self-efficacy, FC = Financial cost.

The results suggest that there is a strong and statistically significant correlation between "Attitude Towards Using AI-RHM" and acceptance (r = 0.79, p < .001) (see Table 4). The implication is that individuals who perceive AI-RHM more positively are more likely to accept it.

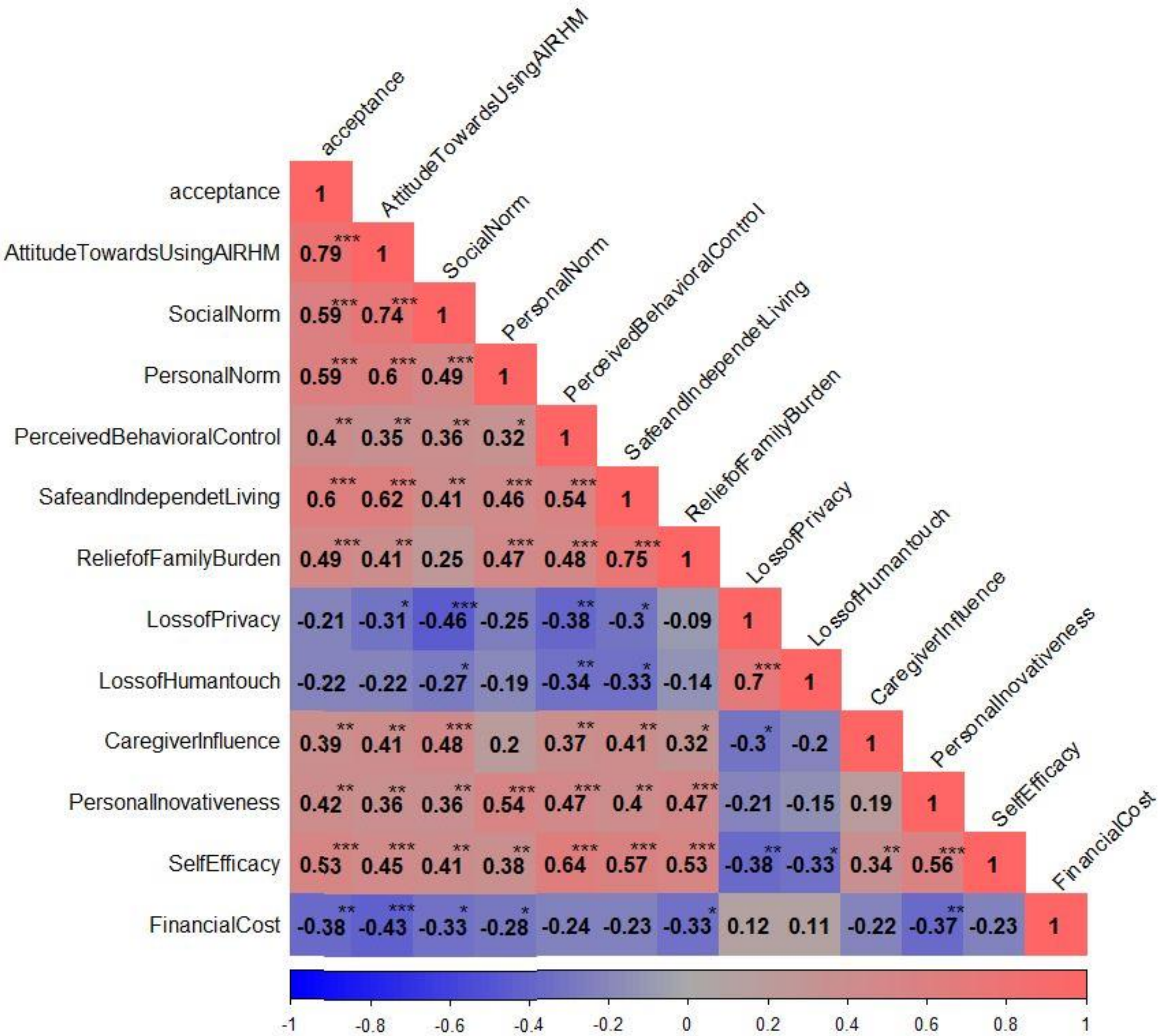
Similar patterns were observed for "Social Norm" (r = 0.59, p < .001) and "Personal Norm" (r = 0.59, p < .001), with both variables showing statistically significant positive correlations with acceptance. These findings suggest that societal and personal norms about AI-RHM usage strongly influence individuals' acceptance.

Further analysis revealed statistically significant positive correlations between acceptance and "Perceived Behavioral Control" (r = 0.40, p < .01), "Safe and Independent Living" (r = 0.60, p < .001), "Relief of Family Burden" (r = 0.49, p < .001), "Caregiver Influence" (r = 0.39, p < .01), "Personal Innovativeness" (r = 0.42, p < .01), and "Self-Efficacy" (r = 0.53, p < .001). This indicates that these factors all positively predict AI-RHM acceptance.

Looking at “Loss of human touch” (r = -0.22, p = n.s.) and “Loss of privacy” (r = -0.21, p = n.s.) it was found that both beliefs have a negative correlation with acceptance and are the only beliefs with no significant effect.

Table 4

Spearman's rank correlation of acceptance and beliefs

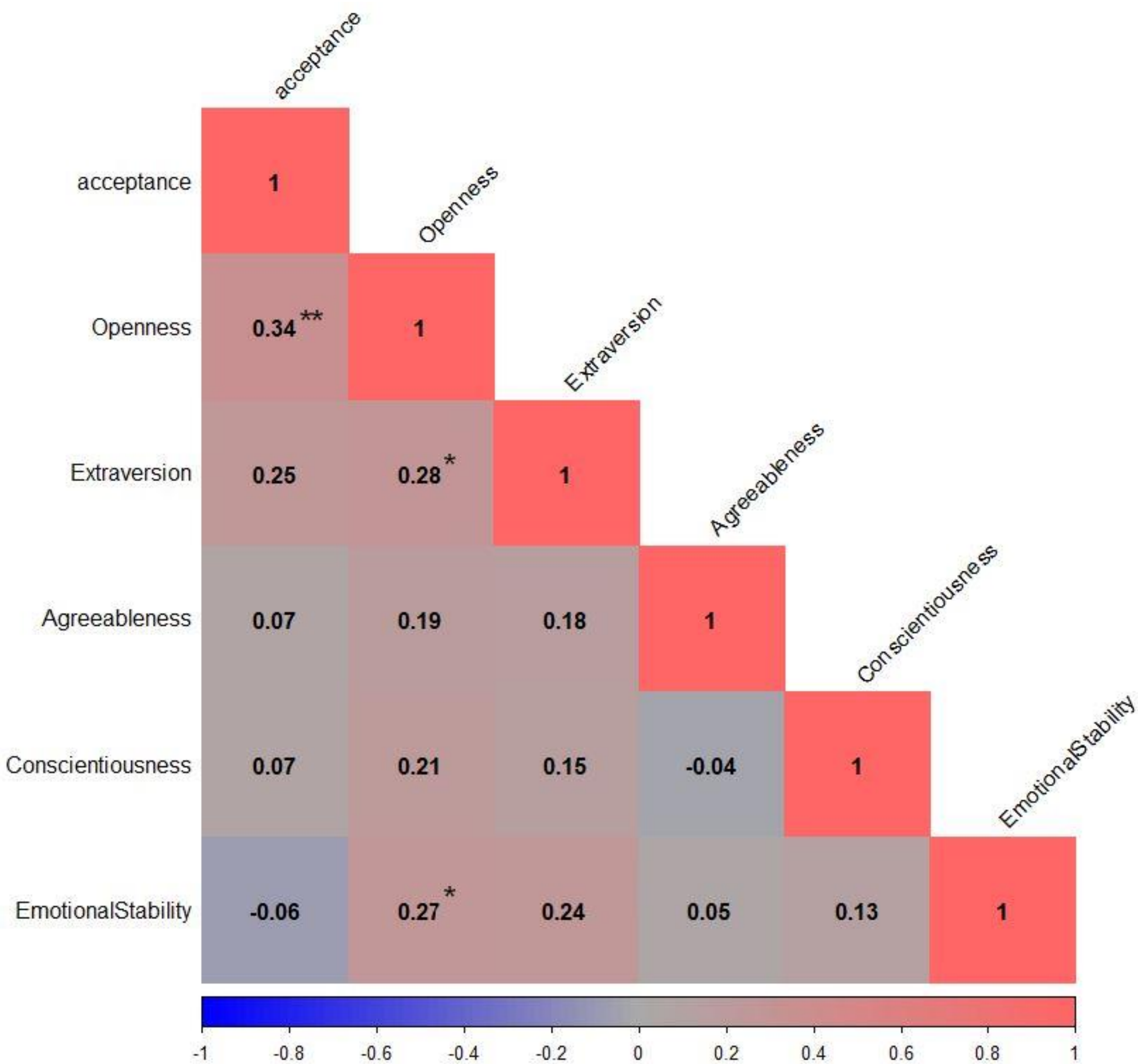


Note. * = p < .05, ** = p < .01, *** = p < .001

Regarding the third research question a statistically significant correlation was observed in the sample between the variables of acceptance and openness, with a low positive correlation coefficient of 0.34 ($p < .01$). This suggests that as levels of openness were increased, levels of acceptance tended to increase as well.

Table 3

Spearman's rank correlation of Personality traits and Acceptance



Note. * = p < .05, ** = p < .01, *** = p < .001

Discussion

Summarizing the study results

The findings from this study shed light on several interesting aspects related to the acceptance of artificial intelligence-based remote health monitoring (AI-RHM) in the context of elderly care among Germans who are aged 45 years and above.

Regarding the first research question, it was found that, on average, the participants are not completely rejecting the idea of AI-RHM, but they are not entirely accepting it either. It was more like this sample was indifferent regarding accepting AI-RHM.

Regarding the second research question, it was found that, only two beliefs have shown no significant effect on personality, namely “Loss of privacy” and “Loss of human touch”. In addition to these two beliefs negatively effecting acceptance a third belief “Financial cost” was negatively associated with acceptance. However, the main finding was that “Attitude towards AI-RHM” was having the biggest impact on acceptance levels. Other huge contributors to acceptance levels were also found such as “Safe and independent living”, “Social norm”, “Personal Norm”, and “Self-efficacy”.

Looking into personality traits, participants have shown high levels of openness and this personality trait showed a significant positive connection with the acceptance of AI-RHM. As openness levels went up, the levels of acceptance did too. This means that participants who are more open to experiences may also be more likely to accept the idea of using AI-RHM.

The study of Jaschinski et al. (2021) have found an acceptance score of ambient assisted living which is 0.39 points higher than the acceptance score of this studies sample for AI-RHM. This could be due to the different way of presenting the technology with only text and a picture, which was different than in the study of Jaschinski et al. (2021). In the original study a short video clip was shown where the researchers have introduced the technology in a storyline. This could have positively affected acceptance rates because they participants get a more vivid picture of the technology and may could better picture a scenario of its advantages. Another reason could be the regional differences. The mentioned study took place in the Netherlands, while this study was carried out in Germany. In the realm of eHealth innovation and technological adoption, the Netherlands prominently stands as a leading force (HIMSS Europe, 2018).

Regarding the second main findings, it can be said that the directions of the beliefs are all in line with previous research and underline the importance and correctness of the acceptance model of Jaschinski et al. (2021). What is also in line with previous research is that “Attitude towards AI-RHM” had the biggest impact on acceptance levels. However, there were differences between the results of this study and the before mentioned study. For this sample there was not found a significant relationship between “Loss of Privacy” and “Loss of human touch” towards acceptance of AI-RHM, which contrasts with the findings of Jaschinski et al. (2021). This difference could be because in this study both variables were correlated directly to acceptance, while in the previous study a mediation effect of both variables on “Attitude towards using AAL” (in this study AI-RHM) was examined. This mediation effect makes the results difficult to compare to each other.

Regarding the third main findings of this study. There are no scientific articles which explored the role of personality in acceptance of AI-RHM or related technologies. However, a review article (Riedl, 2022) found that personality traits affect trust in artificial intelligence which is in turn a crucial foundation for acceptance and adoption. Thus, personality has an indirect effect of acceptance. The findings that openness has a positive effect on acceptance were in line with previous research. In contrast to previous research (Riedl, 2022), extraversion, conscientiousness, and agreeableness have shown a low or no significant relationship with acceptance. This could be due to the low sample size (N = 57) of this study or that personality was assessed with a direct relationship in this study.

Strength and Limitations

One of the strengths of this study is using a quantitative approach to answer the research questions. Thus, the answer was straightforward and could give clear insights into personality traits and the effects on acceptance. Moreover, the scales used for assessing acceptance have shown to have a good explanatory power determining acceptance. Also, the sample showed a relatively low mean age which is good for considering acceptance for future generations. However, there were some limitations in this study as well. Firstly, the relatively low mean age of the sample has also its downsides. Since this technology was specifically designed for elderly people with pre-existing chronic diseases, the age of this sample could distort the representative of the target population. In addition, most participants did not receive homecare and do not have the need for this technology. In addition, this sample consisted only of German citizens which make the findings not generalizable. A second limitation is the reliance on self-report measures, which are subject to biases such as social desirability and recall. Participants may have provided responses they believed were expected or may have inaccurately recalled their personality or beliefs asked in this study. For example, the author was helping one participant to fill in the survey, due to vision impairment, it was noticed that the personality levels the participant was mentioning were not in line with the personality levels relatives would have rated her. A third major limitation is that the participants were only exposed to a picture of the technology and a text describing the applications and advantages of AI-based remote health monitoring. Without direct interaction and hands-on experience with the technology, participants' perceptions may be influenced by their imagination. This could be the case because the technology was not clearly enough introduced to participants, leaving room for speculation and assumptions about its capabilities and limitations.

Future research

Addressing the limitations, future research could benefit from a more diverse sample. As this study was limited to German citizens with a relatively low mean age, the findings may not be generalizable to other cultural or age groups. Therefore, future studies should aim to include participants from a broader range of ages and cultural backgrounds. This would provide a more comprehensive understanding of acceptance across different demographics. Simultaneously, this would allow for a more accurate representation of the target population - elderly people with pre-existing chronic diseases. Secondly, future research could incorporate alternative methods of data collection to mitigate biases associated with social desirability and recall. For instance, future research could consider triangulating data by using observational methods or obtaining feedback from close relatives or caregivers to validate the self-reported personality traits and beliefs of the participants. Thirdly, to overcome the issue regarding the use of imagination in understanding the technology in this study, future research should look to incorporate more interactive approaches that allow participants to directly interact with the technology. Hands-on experience with the technology could help to provide more accurate insights into the participants' acceptance of the AI-based remote health monitoring system. This could include realistic demonstrations, simulations, or even short-term trials where participants can use the technology in their daily lives. Lastly, it could also be beneficial for future research to explore the influence of personality traits on acceptance in greater depth, given the potential discrepancy noted between participant self-report and third-party observations in this study.

Implications

Based on the results of this study several implications can be drawn. Firstly, the study provides evidence that openness could play a role in the acceptance of AI-RHM. The most influential contributor to acceptance of AI-RHM is “Attitude towards AI-RHM”. Taking personality and the most influential beliefs into account, intervention aiming to enhance acceptance and therefore adoption rates could use this knowledge to maximize efficiency and effectiveness. With the use of Rogers theory “diffusion of innovations” (1995) this knowledge could be used to target the first group of a movement the “innovators” which would be people who already show high values in openness and have a good attitude towards AI-RHM. In theory the innovators would then further spread their knowledge and enthusiasm about this technology to the latter adoption groups, starting a movement. In addition, the theory shows an explanation to how new ideas or technologies, like AI-RHM, are processed and adopted. This process is split into five stages: learning about it (knowledge), forming a viewpoint (persuasion), making a choice to use it or not (decision), putting it to use (implementation), and finally deciding to continue using it (confirmation) (Rogers, 1995). Openness to learning new things helps in the initial stage. So, if a person is high in openness, they are more likely receptive to AI-RHM, they'll likely seek more information about it. Making this easier involves providing resources that are easy to use and understand, which can increase comfort with the concept of AI-RHM. The next big factor is attitude, which significantly influences AI-RHM acceptance. During the persuasion stage, an individual develops a positive or negative opinion about the new tech. A positive attitude towards AI-RHM increases the likelihood of choosing to use it. Hence, shaping positive attitudes is crucial. This can be achieved by highlighting the benefits of AI-RHM, addressing any worries, and debunking existing myths. By doing so, the chances of AI-RHM adoption can be significantly enhanced. For the latter stages it could be beneficial to help people with knowledge and tips and tricks to enhance their self-efficacy, that users´ will have a better experience and keep on using AI-RHM.

In addition, it was found that lower acceptance of AI-RHM compared to a previous study on ambient assisted living may suggest that regional factors impact acceptance. This highlights the need for more comprehensive models of acceptance that account for these variables or the need to examine what contributes to these regional differences.

Conclusion

The study explored the acceptance of AI-RHM in elderly care among Germans. The participants were neither completely rejecting nor entirely accepting AI-RHM, showing a general indifference. The study found that Attitude is one of the most influential significant factors regarding acceptance levels. In addition, the study found that the personality trait of openness had a significant positive connection with the acceptance of AI-RHM. As openness levels increased, so did acceptance levels. This suggests that individuals who are more open to experiences may also be more likely to accept the idea of using AI-RHM. The study also identified several limitations. The sample was limited to German citizens with a relatively low mean age, which may not be representative of other cultural or age groups. The study relied on self-report measures, which are subject to biases such as social desirability and recall. Future research could benefit from a more diverse sample and alternative methods of data collection to mitigate these biases. The study's implications suggest that interventions aiming to enhance acceptance and adoption rates could use this knowledge to maximize efficiency and effectiveness. The study also highlights the need for more comprehensive models of acceptance that account for regional differences. In conclusion, the study suggests that Attitude, other beliefs of the model of Jaschinski et al. (2021) and openness, play a significant role in the acceptance of AI-RHM. However, more research is needed to fully understand the factors influencing acceptance, including regional differences and the potential impact of direct interaction with the technology.

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Appendix A

Table 7

Introduction to the Survey in English and German, respectively.

Dear participant,

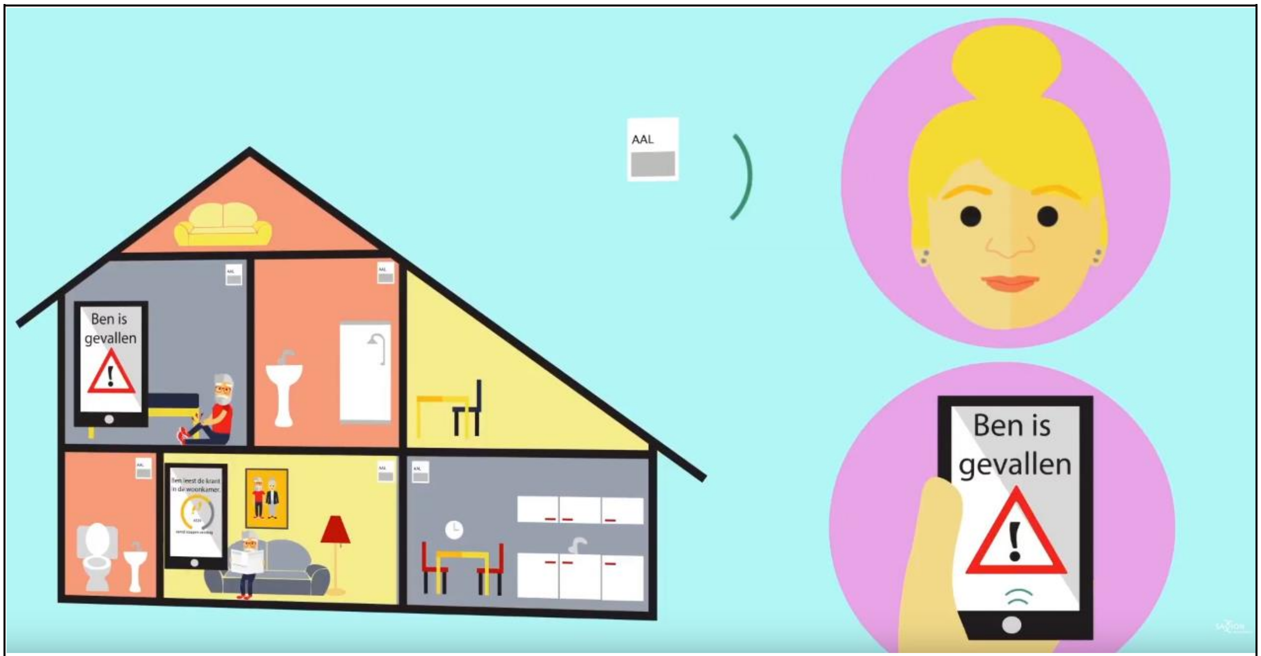
Thank you for participating in this research! Before we begin you will receive information about the research and your rights. Taking part in this research is voluntary and you can withdraw at any moment. Withdrawing will not have negative consequences for you. When doing this survey please use a computer or laptop!

What is AI based health-monitoring (AI-RHM)

AI-based health monitoring is an innovative technology that utilizes artificial intelligence (AI) to track and analyze various aspects of an individual's health. AI is a type of technology that uses machine learning to learn from patterns and data collected and mimic human decision making. With AI-RHM, a discreet sensor is placed in each room to detect and localize movement, daily activities, personal presence, speed/velocity of movement, and breathing. The sensors use existing Wi-Fi waves, which are already present in your home, to collect this data.

When a person moves, the sensor detects the disruption in the Wi-Fi waves, and the data collected is fed into the AI. The AI then compares the collected data to the individual's baseline health information and can determine if there is a deviation from the norm. If needed, the system can alert designated family members or caregivers to provide prompt assistance and timely intervention. For individuals with dementia who may struggle with remembering medication intake or exhibit unusual behavior, such as leaving the house for an extended period, the system can alert caregivers or family members to provide timely care and support.

Overall, AI-based health monitoring can improve the quality of life for older adults, with or without health conditions, by reducing hospital visits and providing timely support in case of emergencies or medication management. The system is non-intrusive and does not require any wearables. The installation cost is around 10,000 Euro. By utilizing this technology, older adults can maintain their independence while ensuring that their health and safety are being monitored.



In the picture you can see a sensor in each room and the potential to notify a family member or carer in an emergency.

Purpose of the research

The study explores the acceptance towards an innovative monitoring technology for aging in place of older adults. This study will explore what factors are associated with acceptance towards innovative monitoring technology. This can help to create products that are tailored to the target audience, leading to better user experiences and higher adoption rates.

Content of the research

Taking part in this research consists of different components. After reading all this information I will ask you to read the "informed consent" section and will ask if you agree and want to proceed. Afterwards, you will be asked about your demographics.

Data processing

The data of this research will be used to determine the level of acceptance of elderly individuals towards remote health monitoring technology and to see what factors are associated with their acceptance. Your data will be anonymized and cannot be traced back to you. Your data will not be shared with third parties. This research is approved by the Ethics Committee of the University of Twente.

You can navigate this survey by clicking the arrows at the bottom of the page. To proceed, please click on the arrow on the bottom right.

Lieber Teilnehmer,

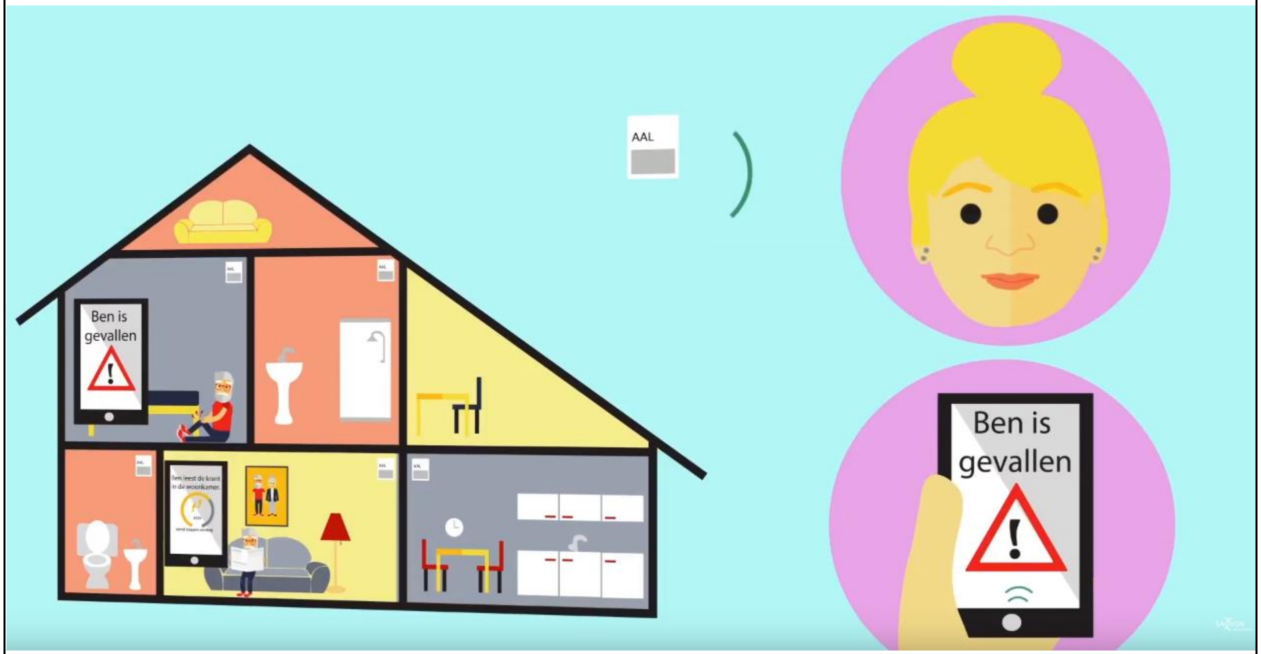
vielen Dank, dass Sie an dieser Untersuchung teilnehmen! Bevor wir beginnen, erhalten Sie Informationen über die Untersuchung und Ihre Rechte. Die Teilnahme an dieser Untersuchung ist freiwillig und Sie können jederzeit zurücktreten. Ein Rücktritt hat keine negativen Folgen für Sie. Bitte benutzen Sie für diese Umfrage einen Computer oder Laptop!

Was ist KI-basierte Gesundheitsüberwachung (AI-RHM)?

KI-basierte Gesundheitsüberwachung ist eine innovative Technologie, die künstliche Intelligenz (KI) nutzt, um verschiedene Aspekte der Gesundheit einer Person zu verfolgen und zu analysieren. KI ist eine Technologie, die maschinelles Lernen einsetzt, um aus gesammelten Mustern und Daten zu lernen und die menschliche Entscheidungsfindung zu imitieren. Bei AI-RHM wird in jedem Zimmer ein diskreter Sensor angebracht, der Bewegungen, tägliche Aktivitäten, persönliche Anwesenheit, Bewegungsgeschwindigkeit und Atmung erkennt und lokalisiert. Die Sensoren nutzen vorhandene Wi-Fi-Wellen, die bereits in Ihrer Wohnung vorhanden sind, um diese Daten zu erfassen.

Wenn sich eine Person bewegt, erkennt der Sensor die Unterbrechung der Wi-Fi-Wellen, und die erfassten Daten werden an die KI weitergeleitet. Die KI vergleicht dann die gesammelten Daten mit den grundlegenden Gesundheitsinformationen der Person und kann feststellen, ob es eine Abweichung von der Norm gibt. Bei Bedarf kann das System Familienmitglieder oder Pflegekräfte alarmieren, um sofortige Hilfe und rechtzeitiges Eingreifen zu ermöglichen. Bei Demenzkranken, die Schwierigkeiten haben, sich an die Medikamenteneinnahme zu erinnern, oder die ein ungewöhnliches Verhalten an den Tag legen, wie z. B. das Verlassen des Hauses für einen längeren Zeitraum, kann das System Pflegekräfte oder Familienmitglieder alarmieren, damit diese rechtzeitig Hilfe und Unterstützung leisten.

Insgesamt kann die KI-basierte Gesundheitsüberwachung die Lebensqualität älterer Erwachsener mit oder ohne gesundheitliche Probleme verbessern, indem sie die Zahl der Krankenhausaufenthalte verringert und bei Notfällen oder der Medikamenteneinnahme rechtzeitig Unterstützung bietet. Das System ist nicht invasiv und erfordert keine Wearables. Die Installationskosten belaufen sich auf etwa 10.000 Euro. Durch den Einsatz dieser Technologie können ältere Menschen ihre Unabhängigkeit bewahren und gleichzeitig sicherstellen, dass ihre Gesundheit und Sicherheit überwacht werden.



Zweck der Studie

Die Studie erforscht die Akzeptanz einer innovativen Überwachungstechnologie für das Altern an Ort und Stelle bei älteren Erwachsenen. In dieser Studie wird untersucht, welche Faktoren mit der Akzeptanz innovativer Überwachungstechnologie verbunden sind. Dies kann dazu beitragen, Produkte zu entwickeln, die auf die Zielgruppe zugeschnitten sind, was zu besseren Nutzererfahrungen und höheren Akzeptanzraten führt.

Inhalt der Studie

Die Teilnahme an dieser Studie besteht aus verschiedenen Komponenten. Nachdem Sie all diese Informationen gelesen haben, werde ich Sie bitten, den Abschnitt " Einverständniserklärung" zu lesen, und Sie fragen, ob Sie damit einverstanden sind und fortfahren möchten. Danach werden Sie zu Ihren demografischen Daten befragt.

Verarbeitung der Daten

Die Daten dieser Studie werden verwendet, um den Grad der Akzeptanz älterer Menschen gegenüber der Technologie zur Fernüberwachung ihrer Gesundheit zu ermitteln und um festzustellen, welche Faktoren mit ihrer Akzeptanz zusammenhängen. Ihre Daten werden anonymisiert und können nicht zu Ihnen zurückverfolgt werden. Ihre Daten werden nicht an Dritte weitergegeben. Diese Forschung wurde von der Ethikkommission der Universität Twente genehmigt.

Sie können durch diese Umfrage navigieren, indem Sie auf die Pfeile am unteren Rand der Seite klicken. Um fortzufahren, klicken Sie bitte auf den Pfeil unten rechts.

Appendix B

Table 8

Informed Consent in English and German, respectively.

Consent Form **Taking part in the study** I have read and understood the study information. I voluntarily take part in this research and understand that I can't refuse to answer questions. I understand that I can withdraw from this study at any time, without having to give a reason. I understand that I must answer the survey questions as truthfully as possible. I am at least 45 years old. **Use of the information in the study** I understand that providing demographic data, reading the instruction thoroughly, and filling in the questionnaires afterwards is also part of the study. **Future use and reuse of the information by others** I understand that the information I will enter will be used for a bachelor thesis. I understand that the information I provide will be anonymized and then stored in a secure environment. I consent to the fact that the anonymized information provided by me is kept for use in future studies. **Contact information for questions about Your rights as a participant** **If you ever have any questions regarding your participation in this study, you can email** s.stahl-1@student.utwente.nl. If you have any questions about your rights as a participant, the use of your data, or other questions and concerns about this research, you can contact the secretariat of the Ethics Committee of the Faculty of Behavioural, Management, and Social Sciences of the University of Twente: ethicscommittee-bms@utwente.nl. **Do you consent to participating in this research?**
Einverständniserklärung

Teilnahme an der Studie

Ich habe die Informationen zur Studie gelesen und verstanden. Ich nehme freiwillig an dieser Studie teil und verstehe, dass ich die Beantwortung von Fragen nicht verweigern kann. Mir ist bekannt, dass ich jederzeit von dieser Studie zurücktreten kann, ohne einen Grund angeben zu müssen. Mir ist bekannt, dass ich die Fragen der Umfrage so wahrheitsgemäß wie möglich beantworten muss. Ich bin mindestens 45 Jahre alt.

Verwendung der Informationen in der Studie

Mir ist bekannt, dass die Angabe demografischer Daten, das gründliche Lesen der Anleitung und das anschließende Ausfüllen der Fragebögen ebenfalls Teil der Studie sind.

Künftige Nutzung und Wiederverwendung der Informationen durch andere

Mir ist bekannt, dass die von mir eingegebenen Informationen für eine Bachelorarbeit verwendet werden. Mir ist bekannt, dass die von mir gemachten Angaben anonymisiert und anschließend in einer sicheren Umgebung gespeichert werden. Ich erkläre mich damit einverstanden, dass die von mir angegebenen anonymisierten Daten zur Verwendung in zukünftigen Studien aufbewahrt werden.

Kontaktinformationen für Fragen zu Ihren Rechten als Teilnehmer

Wenn Sie Fragen zu Ihrer Teilnahme an dieser Studie haben, können Sie sich per E-Mail an s.stahl-1@student.utwente.nl wenden. Wenn Sie Fragen zu Ihren Rechten als Teilnehmer, zur Verwendung Ihrer Daten oder zu anderen Fragen und Anliegen im Zusammenhang mit dieser Studie haben, können Sie sich an das Sekretariat der Ethikkommission der Fakultät für Verhaltens-, Management- und Sozialwissenschaften der Universität Twente wenden: ethicscommittee-bms@utwente.nl.

Sind Sie mit der Teilnahme an dieser Studie einverstanden?

Appendix C

Table 9

Demographic Data in English and German, respectively.

Gender (assigned at birth)

- Male
- Female
- Other: _____

How old are you in years (e.g., 45 or 63)

- __________

What is your nationality?

- Dutch
- German
- Other: ___________

What is your english skill and comprehension (0 = non speaker, 100 = native speaker)

- ________

What is your current living situation?

- I am living alone
- I live with someone else (e.g., partner or family)

Do you receive home care?

- Yes
- No

I currently use technologies for tracking health and vital signs like smartwatches, sleeping rings etc.:

- No
- Yes, please specify: ______

Geschlecht (bei der Geburt zugewiesen)

- Männlich
- Weiblich

- Andere: ____________

Wie alt sind Sie in Jahren (z. B. 45 oder 63)

- ___________

Welche Nationalität haben Sie?

- Niederländisch
- Deutsch
- Andere: ____________

Wie gut sind Ihre Deutschkenntnisse und Ihr Verständnis (0 = Nicht-Sprecher, 100 = Muttersprachler)

- _________

Wie ist Ihre derzeitige Lebenssituation?

- Ich lebe allein
- Ich lebe mit einer anderen Person zusammen (z. B. Partner oder Familie)

Werden Sie zu Hause gepflegt?

- Ja
- Nein

Ich verwende derzeit Technologien zur Überwachung von Gesundheit und Vitalfunktionen wie Smartwatches, Schlafringe usw.:

- Nein
- Ja, bitte erläutern: _______

Appendix D

Table 10

Task explanation in English, German, and Dutch, respectively.

Task explanation Welcome to the main questionnaire. We kindly request that you answer the questions as honestly as possible. If you do not require elderly care, please imagine that you do and answer accordingly. If you were in need of a caregiver, would you consider using this technology? We will begin by asking you 10 questions about your personality, followed by questions about your attitudes and thoughts towards this technology.
Erläuterung der Aufgabe Willkommen zum Hauptfragebogen. Wir bitten Sie, die Fragen so ehrlich wie möglich zu beantworten. Wenn Sie nicht pflegebedürftig sind, stellen Sie sich bitte vor, dass Sie pflegebedürftig sind und antworten Sie entsprechend. Wenn Sie eine Betreuungsperson benötigen würden, würden Sie diese Technologie in Betracht ziehen? Wir werden Ihnen zunächst 10 Fragen zu Ihrer Persönlichkeit stellen, gefolgt von Fragen zu Ihrer Einstellung und Ihren Gedanken zu dieser Technologie.

Appendix E

Table 5

Personality Test Ten Item Personality Measure (TIPI) in English and German, respectively.

Please indicate to what degree you agree with each of the following statements (measured with a seven-point Liker scale (Strongly disagree – strongly agree)) I see myself as: • Extraverted, enthusiastic • Critical, quarrelsome • Dependable, self-disciplined • Anxious, easily upset • Open to new experiences, complex • Reserved, quiet • Sympathetic, warm • Disorganized, careless • Calm, emotionally stable • Conventional, uncreative
Bitte geben Sie an, inwieweit Sie jeder der folgenden Aussagen zustimmen (gemessen mit einer siebenstufigen Liker-Skala (stimme überhaupt nicht zu - stimme voll und ganz zu)) Ich sehe mich selbst als: • Extravertiert, begeistert • Kritisch, streitsüchtig • Zuverlässig, selbstdiszipliniert • Ängstlich, leicht aus der Fassung zu bringen • Offen für neue Erfahrungen, vielschichtig • Zurückhaltend, still • Verständnisvoll, warmherzig • Unorganisiert, achtlos • Gelassen, emotional stabil • Konventionell, unkreativ

Appendix F

Table 5

Conceptual model of ambient assisted living acceptance (Jaschinski et al., 2021) *in English and German measured with a 5-point Likert scale.*

Intention to use AI-RHM Technology: • In the future, I plan to use AI-RHM technology. • In the future, I expect to use AI-RHM technology. • In the future, I intend to use AI-RHM technology. • I would recommend other people to use AI-RHM technology. **Attitude towards using AI-RHM Technology:** • Using AI-RHM technology is a (good/bad) idea. • Using AI-RHM technology is (wise/foolish). • Using AI-RHM technology is (valuable/worthless). • I (like/dislike) the idea of using AI-RHM technology. • Using AI-RHM technology is (pleasant/unpleasant). • Using AI-RHM technology is (enjoyable/unenjoyable) **Social norm:** • Most people who influence me would have a positive opinion towards my use of AI-RHM technology. • Most people who are important to me would have a positive opinion towards my use of AI-RHM technology. • Most people whose opinion I value would think positively about my use of AI-RHM technology. **Personal norm:** • I view myself as a user of technology for my health and well-being. • I think of myself as someone who is very interested in technology for health and well-being. • I am not the type of person oriented to use technology for my health and well-being.

Perceived behavioral control:

- I would be able to use AI-RHM technology.
- Using AI-RHM technology is entirely in my control.
- I have the resources and opportunities it takes to make use of AI-RHM technology.
- I have the knowledge it takes to make use of AI-RHM technology.

Safe and independent living:

- Using AI-RHM technology will give me a sense of security.
- If I use AI-RHM technology, I will feel safer in my home.
- If I use AI-RHM technology, accidents at home will be noticed immediately.
- With the help of AI-RHM technology, I will receive immediate help in case of emergencies.
- Using AI-RHM technology will allow me to age in my home environment.
- If I use AI-RHM technology I can keep doing things on my own.
- If I use AI-RHM technology I can do things independently.

Relief of Family Burden:

- My use of AI-RHM technology, will give my family members peace of mind.
- If I use AI-RHM technology, my family members will be less concerned.
- If I use AI-RHM technology, my family members will have more time for themselves.
- My use of AI-RHM technology will relieve the burden on my family members.

Loss of privacy:

- If I use AI-RHM technology, I am concerned that others might use my personal information to harm me.
- If I use AI-RHM technology, I worry that my personal information might be shared with others without my permission.
- If I use AI-RHM technology, I worry to be constantly monitored.
- If I use AI-RHM technology, I am concerned that my social interactions will be monitored.

- Using AI-RHM technology will feel like an invasion into my personal space.
- If I use AI-RHM technology, I am concerned that intimate situations will be monitored.

Loss of human touch:

- If I use AI-RHM technology, people will visit me less often.
- If I use AI-RHM technology, I will receive less personal care.
- Using AI-RHM technology, I will get less personal attention.
- Using AI-RHM technology will replace human contact.

Caregiver Influence:

- My caregivers would have a positive opinion towards my use of AI-RHM technology.
- My caregivers would have a positive view on my use of AI-RHM technology.
- My caregivers would value my use of AI-RHM technology.

Personal innovativeness

- If I heard about a new information technology, I would look for ways to experiment with it.
- In general, I am hesitant to try out new information technologies.
- Among my peers, I am usually the first to try out new information technologies.
- I like to experiment with new information technologies.

Self-efficacy

- I feel confident about using AI-RHM technology.
- I feel confident I know how to learn advanced skills related to using AI-RHM technology.
- I feel confident understanding terms/words relating to AI-RHM technology.
- I would avoid AI-RHM technology because it is unfamiliar to me.
- I hesitate to use AI-RHM technology for fear of making mistakes I cannot correct.

Financial Cost

• It will cost a lot to use AI-RHM technology. • There are financial barriers to my use of AI-RHM technology. • I think that using AI-RHM technology will be expensive.