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Tying mobile health tools to the users' needs – Motivational drivers

A descriptive cross-sectional study

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Abstract

Objective: The primary aim of this thesis is to contribute novel insights into the distinctive attributes of ICT systems, with a particular emphasis on features preferred by users in the realm of mobile health (mHealth) applications and devices. The study aimed at identifying motivational factors that enhance and sustain the usage and adaption of mHealth applications, wearables, and trackers among both healthy individuals and those affected by chronic diseases (sickle cell and diabetes).

Methods: In total, 584 participants completed the survey and answered the specific questions important for this thesis. A descriptive analysis of the demographics as well as regular use of tracking technologies and of the most motivating features of wearable sensors was performed. Further, the approach of binary logistic regression was applied to investigate the association between the importance of specific features and age, gender and health status.

Results: The descriptive analysis revealed that relevant personalized feedback and the ease of use of mobile health apps, wearables and trackers represent the most motivating features for a prolonged use. The logistic regression analysis revealed a statistically significant and positive association between having a chronic disease, age, gender, and the importance of notifications of mobile phones and managing a condition. The point estimates for several features like sensor accuracy and range of values as well as ergonomic and design and personalized/tailored features indicated a positive association between people with chronic diseases, age and gender. But these results were inconclusive.

Conclusion: This study provided valuable insight into the motivational drivers and adoption patterns of mobile Health applications and wearable devices among young and elderly individuals with and without chronic diseases. However, external validity and generalizability of the results was not given due to study limitation and low statistical power. Further research is therefore needed.

Keywords: mHealth, motivation, long-term engagement, user preferences, mobile health applications, wearable devices, diabetes, sickle cell disease

Abbreviations

CI	Confidence Interval
CDC	Centers for Disease Control and Prevention
eHealth	Electronic health
GPS	Global Positioning System
mHealth	Mobile Health
PDA	Personal Digital Assistants
ICT	Information and Communication Technology
NSD	Norwegian Data Protection Authority/ Norwegian: Datatilsynet
OR	Odds Ratio
PAHO	Pan American Health Organization
REK	Regional Committee of Medical and Health Research Ethics Norwegian: Regionale komiteer for medisinsk og helsefaglig forskningsetikk
SMS	Short Message service
VIF	Variance Inflation Factor
WHO	World Health Organization

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1 Introduction

1.1 Background and context

The increasing importance of the broad field of public health is evident in a world where challenges arise from infectious diseases and their prevention, as well as the need for new treatments for non-communicable diseases. (Abdulrahman & Ganasegeran, 2019, p.171; Tulchinsky &Varavikova, 2014, pp.43-45) At the center stands the challenge of focusing on the people affected, identifying their needs and tailoring interventions accordingly (Abdulrahman & Ganasegeran, 2019, p.179).

In the 21st century, the world offers both a rich amount of knowledge and resources in healthcare. But according to Kwankam, overcoming the gap between unnecessary human pain and hardship and seizing the opportunity to deliver good health is a major challenge (Kwankam, 2004, p.800). The persistence of this challenge can be attributed to the gap between knowledge and action in healthcare, as highlighted by a former Director-General of the World Health Organization. Lee Jong-wook:

"*The application of today's scientific advancements is hindered by a gap between knowledge and action. In the field of healthcare, this gap is particularly evident, as demonstrated by the rigorous teachings of health work. It is widely recognized that action without knowledge is futile, just as knowledge without action is a wasted resource (Lee Jong-wook, WHO, 2006, p.1)".*

According to the World Health Organization (WHO), the field of e-health and its digital technologies may be able to revolutionize how knowledge in health and health services can be accessed (WHO, 2018, p.2). Facilitating quick sharing of information through the internet opened major opportunities in these regards (Bhattacharya et al., 2018, p.56).

Beside the group of healthcare professionals, it is mostly laypersons who benefit from the new innovations. The term "layperson" is defined as individuals without specialized knowledge in a particular field, such as health. This includes patients, caregivers, or the general public seeking health information without a professional healthcare background (Cambridge University Press & Assessment, 2023). With the rapidly growing amount of health information, scanning through and identifying the most relevant facts is a complex task (Kwankam, 2004, p.800).

Information and communication technology (ICT) systems may have the potential to aid individuals in navigating through the existing data on health, supporting a higher degree of health literacy (Kwankam, 2004, pp.800-801).

Prior to delving into the subject matter, it is important to acknowledge that the motivation of individuals to actually adapt these technologies is likely to be a key driver. Motivation and high interest rates might potentially contribute to the long-term use of mHealth applications. However, despite its significance, there is still limited understanding of the specific factors that motivate individuals in this context (Jaana & Paré, 2020).

The primary objective of this thesis is to contribute novel insights into the distinctive attributes of ICT systems, with a particular emphasis on features preferred by users in the realm of mobile health (mHealth) applications and devices. The central focus revolves around exploring the motivational factors that drive prolonged usage of such technologies.

1.2 Knowledge gap

As a means of patient empowerment, adaption of mHealth applications are frequently being addressed in medical and public health literature (Lupton, 2012, pp. 230-232; Martinez-Millana et al., 2018). This is due to mHealth applications' ability to provide its users with health related, relevant information and data. The improvement of the users' knowledge regarding their health status can be a positive result, opening the opportunity for a more active involvement in the management of ones' health (Lupton, 2012, p.230). According to the International Telecommunication Union, 66% of the total global population had been connected via the Internet in 2022 which represents approximately 5.3 billion people (ITU, 2022). However, achieving the goal of health promotion through digital pathways requires more than just providing Internet connections and the respective mHealth apps. The main challenge here is the encouragement and dissemination of the active use of mHealth applications on a broad scale. Therefore, in addition to the bare ownership of mobile devices and internet access, providers of mHealth applications need users who download and actively engage with the apps long-term (Vo, Auroy & Sarradon-Eck, 2019).

According to Lupton, as of 2014, one third of the American smartphone users had downloaded health and fitness related applications (Lupton, 2014, p. 609). But according to a review of qualitative studies in 2019, these health care applications are only actively used for a short time after downloading (Vo, Auroy & Sarradon-Eck, 2019). In order to gain a better understanding of user- and patient experiences, their perceptions and needs are sought out in order to facilitate long-term use (Vo, Auroy & Sarradon-Eck, 2019).

While the concept of leveraging technology in order to manage ones' health has seen widespread appeal, it is especially vital for people suffering from chronic diseases. One key element to be considered here is the aging population, which has an increased prevalence of chronic disease (United Nations, 2017). The growing population of elderly people has led to a higher demand of the services provided by healthcare systems. According to a cross-sectional survey from 2020, promoting the use of mHealth technology in an aging population may be a way to address these challenges (Jaana & Paré, 2020).

To achieve this goal, it is important to identify the motivational drivers for using mHealth apps, wearables, and trackers. Both amongst healthy people and patients with chronic diseases, and in young and older age groups, to enable the use of the apps on a long-term basis (Jaana & Paré, 2020).

1.3 Significance of mobile health in the field of public health

E-health is considered one of the fastest growing fields in nowadays health care (Da Fonseca, et al., 2021). Due to their wide acceptance, broad reach, and ease of use, digital technologies represent an important resource in the field of public health (WHO, 2018).

In the recent years, the development of mobile health applications and their adaption have increased the access to services, information, and skills. Mobile wireless technologies influenced the landscape of healthcare in several areas. They contributed to a higher quality of care and availability of services, paving the way towards universal health coverage. Mobile health further helped to prevent the onset of chronic and acute disease by promoting health behavior and lifestyle changes (WHO, 2018). Many of these applications and devices facilitate a variety of specific health related support: Some examples could be remote consultations, offering personalized fitness and wellness guidance, aid in medication management, provide mental health support, offering reliable health information or cater to women's health needs.

Overall, mHealth apps bring convenient and accessible resources in various areas (WHO, 2011, pp.19-61; WHO 2019).

Mobile health applications may therefore have the potential to play an important part in creating a patient centered approach on improving health literacy, empowering individuals and further to achieve a global accessibility of services (Salgado, Tavares & Oliveira, 2020).

There is an opportunity for widespread accessibility here, as variations of mHealth technology have already been introduced worldwide. Most people around the globe use smartphones or have access to the internet. This opens the door for the introduction of the latest technologies to improve health service delivery and outcome quality (Vo, Auroy & Sarradon-Eck, 2019).

1.4 Scope

This thesis is based on the "Motivation in mobile Health" study which was conducted by a team consisting of researchers from UiT the Arctic University of Norway, the Norwegian Centre for e-health Research, the University of Geneva, and the Illinois Institute of Technology. Data collection for this project started in November 2018.

The study aimed at identifying motivational factors which are related to an enhanced user engagement on long-term basis and the willingness to share self-collected health data. Scenarios of data integration and data sharing, wearables and sensors and social media and entertainment were investigated (Woldaregay, et al., 2018, pp. 152-153). The underlying questionnaire targeted healthy people as well as people with chronic disease (Henriksen, Pfuhl, et al., 2022, pp. 41-42). Results showed that it is mainly a lack of motivation that prevents users from actively using health applications over a long duration of time (Woldaregay, et al., 2018; Henriksen, Pfuhl, et al. 2022).

For this thesis, previously unused data from the same dataset was utilized. Thus, findings are influenced by the characteristics of this specific study sample. Two chronic diseases were hereby most relevant, *Diabetes mellitus* and *Sickle cell disease*. A chronic disease refers to a long-term medical condition that persists for an extended duration and typically progresses gradually over time. Such conditions, also referred to as noncommunicable diseases, require ongoing management. They can have a substantial impact on a person's well-being, quality of life, and everyday functioning (WHO, 2022).

Diabetes mellitus is a long-term medical condition that arises from the body's inability to either produce or properly use insulin, a hormone responsible for regulating blood sugar levels. Consequently, high levels of glucose accumulate in the bloodstream, which can lead to a variety of health complications if left untreated or unmanaged over time (PAHO, 2022). The main challenges are the increased risk of cardiovascular disease, nerve damage, kidney damage, and blindness (Deshpande, et al. 2008, pp.1257-1260).

Sickle cell disease is an inherited blood disorder that is characterized by the presence of abnormal hemoglobin molecules in red blood cells. This abnormality causes the red blood cells to become rigid and take on a sickle shape, which in turn leads to blockages in the blood vessels (CDC, 2022). Individuals with this condition are at a higher risk of experiencing complications such as stroke, acute chest syndrome, and organ damage, which can be life-threatening (CDC, 2022a). Common for these conditions, a combination of lifestyle measures, like adequate hydration and diet, physical activity, adherence to medication, and the regular monitoring is crucial (Deshpande, et al. 2008, p. 1261-1262; National Heart, Lung, and Blood Institute, 2022)

The availability and use of mobile self-management tools are considered a promising approach to improve treatment adherence for both diabetes and sickle cell disease patients (Tatara, Årsand, et al., 2013; Anderson et al., 2018).

1.5 Main aim and objectives

The master thesis will add to this knowledge by conducting a descriptive cross-sectional study using the data of the "motivation in mobile health" study by Henriksen et al. (Henriksen et al. 2023).

Main aim of this thesis is the identification of motivational drivers of both healthy users and people affected by chronic diseases (sickle cell and diabetes) that increase and prolong the usage and adaption of mHealth applications, wearables and trackers. A further focus will lie on examining the impact of users' demographics (age and gender) and health status on their adoption of mobile health apps and wearables.

By motivational drivers I refer to specific features of mobile health applications and trackers that are valued by the users and thus, directly linked with choosing the devices and encouraging an increased use.

The following research questions will be addressed:

What are the motivational drivers among young and elderly people with and without chronic diseases that have the potential to increase the long-term user adaption of mobile health apps and devices?

Is the likelihood to adopt mobile health apps and wearables influenced by the users' demographics and health status?

2 Theoretical framework

2.1 Defining E-health

To date, there is no uniformly described definition of the term "e-health" that researchers agree on (Oh, et al., 2005; Fatehi &Wootton, 2012, p.460). Several sources describe the domain of electronic health as a connection between a variety of fields (Beuscart et al., 2014, pp. 406-407; Hallberg & Salimi, 2020, pp. 119-120). According to Beuscart et al. e-health stretches from (medical) informatics and telecommunication aspects over to the actual delivery of health care services including personalized health and homecare (Beuscart et al., 2014, p. 405).

In 2001, Eysenbach defined the concept of e-health as an emerging field which focuses on the distribution of health information and services through the Internet or similar technologies. Therefore, the fields of business, public health and medical informatics intersect in e-health (Eysenbach et al., 2001). Kwankam presented a similar definition by describing e-health as "an all-encompassing term for the combined use in the health sector of electronic information and communication technology (ICT) for clinical, educational, research and administrative purposes, both at the local site and at a distance (Kwankam, 2004, Bulletin of the World Health organisation, p.800)".

The world health organization (WHO) stated, that the term can be predominantly described as to apply ICT services and applications in the fields of healthcare (WHO, 2019). The rational of e-health according to WHO hereby does not only lie in supporting health and related fields by increasing efficiency and through reduction in costs, but also in improving health care quality and its access (WHO, 2023).

The concept of mobile health

Mobile health, often known as mHealth can be broadly described as the use of digital, more specified mobile wireless technologies in the medical field and public health (Holman, 2018). It represents an integral part of the broad field of e-health (WHO, 2018).

In 2011 the WHO global observatory for eHealth defined the concept as a combination of public health and medical practices. These are hereby supported by wireless devices such as mobile phones, personal digital assistants (PDAs) and patient monitoring devices. The delivered services of mHealth encompass a vast array of mobile-based solutions – from simple utilities like short messaging services (SMS) to more complex tools like smartphone applications – this includes the use of Bluetooth technology, global positioning systems (GPS) and third and fourth generation mobile telecommunications (3G and 4G systems, respectively) (WHO, 2011).

Bhattacharya et al. have a similar understanding of the term. An example of mHealth tools can hereby be mobile phones and monitoring devices used for the observation of blood glucose levels in diabetes treatment (Bhattacharya, et al., 2018, p.56).

The term of mHealth is not interchangeable with "telehealth". The main difference lies in telehealth being delivered via telecommunication technologies and electronic information, hereby referring to delivering of remote care. Several mobile platforms are therefore in use for telehealth while mobile health services are exclusively delivered via mobile devices (Holman, 2018).

Mobile health applications and devices are most commonly used in the fields of health education, giving information regarding disease prevention and lifestyle changes. Further disease treatment and management mostly of chronic conditions represents a big field of use. Since 2019 due to the Covid-19 Pandemic, infection tracking and surveillance in outbreak scenarios became another important field of application (Vaghefi, et al., 2019; Holman, 2018).

2.2 Defining motivation

The primary focus of this thesis lies on the identification of motivational drivers that enhance and sustain the usage and adoption of mHealth applications, wearables, and trackers among both healthy individuals and those affected by chronic diseases. The aim is to understand the factors that encourage and prolong engagement with these technologies. Thus, a definition of the concept of motivation will be given.

According to the Oxford learners dictionary of academic English, motivation can be defined as follows:

Motivation describes the willingness or desire to do something or reasons for showing a particular behavior" (Oxford University Press, 2023).

The Cambridge dictionary defines the same concept as the enthusiasm to execute a specific action (Cambridge University Press & Assessment, 2023a).

The term originates from the Latin word motivus ("a moving cause"). Hence, the study of motivation is in a simple sense focusing on reasons why an individuum engages in a specific action (Cofer & Petri, 2023). The construct of motivation describes underlying external and/or internal forces that initiate action, further steering the behaviors' direction, intensity and persistence (Sarrazin, et al., 2002, p.396).

In practical settings motivation is a highly valued psychological concept as it has tangible consequences. With it resulting in actions and achievements, it represents a leading agenda for people in the roles of health care professionals, coaches and managers. Understanding and promoting motivation is essential for mobilizing others to engage in productive behaviors (Ryan & Deci, 2000, p.69).

The focus of this thesis is not so much on the concept of motivation in general, but on the factors that motivate people to pursue a goal over a duration of time called long-term motivation. Long-term motivation is the persistent and sustained drive to achieve a goal over a prolonged period. It involves a strong commitment to the goal and the willingness to persistently work towards it, even when faced with challenges (Ryan & Deci, 2017, pp. 37-38).

Motivation can both arise from the individual itself (intrinsic) or be driven by external factors. While intrinsic motivation describes engagement due to an inherent interest in the activity, extrinsic motivation is driven by an expected reward or negative factors such as pressure (Eccles &Wigfield, 2002, p. 112)

Contrary to short-term motivation, which mainly centers around immediate results, long-term motivation is anchored in a profound sense of purpose and significance, driven by a desire to create enduring impacts or attain notable achievements (Latham & Pinder, 2005, p. 502).

To maintain long-term motivation, individuals need to develop various strategies, such as setting challenging and specific goals, cultivating self-efficacy and confidence, building a supportive network of mentors and peers, and engaging in self-reflection and self-care (Bandura, 1997, pp.193-198). By sustaining long-term motivation, individuals can accomplish their goals and experience a sense of personal fulfillment and achievement (Bandura, 1997, pp. 232-233).

In 1990, Edwin Locke and Gary Latham developed their theory of goal-setting and task performance, describing key principles that create motivation and lead to long-term commitment (Locke & Latham, 1991, pp. 480-483). The researchers hereby name values, emotions, intensions (goals) and needs as the key motivational factors (Figure 1).

The theory proposes that both values and the underlying goals determine behavior. An individual's values can generate a strong motivation to engage in behaviors that align with these. Thus, emotions and desires play into the direction of behavior. The pursued goals influence how actions are prioritized, directing one’s behavior to create strategies for persistence and effort. Goals are therefore also a motivational factor for developing new skills. The outcome, accomplishment of the goal or failure may then result in either satisfaction or frustration (Locke, 2000, pp. 411-413; Lunenburg, 2011, p. 2).

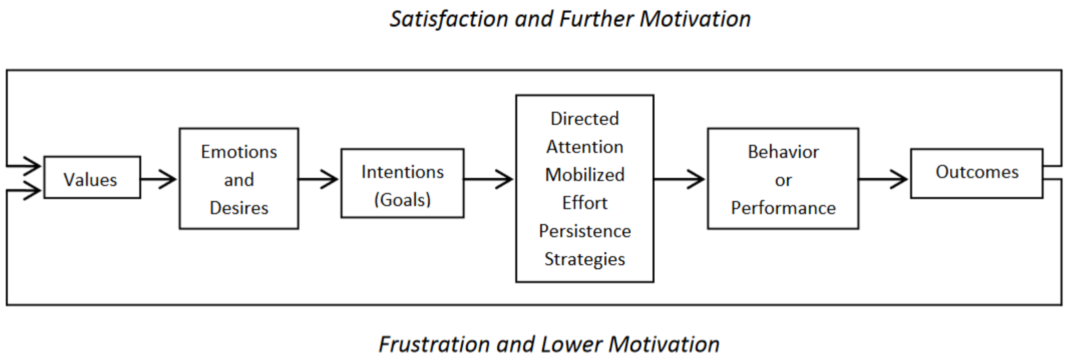


Figure 1: General model of goal-setting theory by Locke and Latham (Lunenburg, 2011, p.2)

According to Locke, maximum performance is typically achieved when an individual has a well-defined and challenging objective that serves as a benchmark for evaluating their performance. Feedback on the result is of high importance as it creates a sense of commitment and acceptance towards the goal (Locke, 2000, p. 415).

Linking the presented information to the underlying study: Identifying the major motivational factors for the facilitation of a prolonged mHealth use may benefit people of all age groups, but especially those affected by chronic diseases.

By incorporating appropriate motivational factors, these systems can be designed to better support an individual's efforts to adopt and maintain healthier behaviors and habits that are aligned with their unique needs and goals (Anderson, et al., 2016).

Individual performance, persistence and task selection may be directly linked to an individual's values and expectations, as proposed by Eccles and Wigfield (Eccles & Wigfield, 2002, pp.115-117). Essentially, an individual's values and expectations can shape the types of tasks they pursue, how long they persist in completing them, and their overall success in achieving their goals (Eccles & Wigfield, 2002, pp.115-117).

3 Material and Methodology

3.1 Study population and data collection

Data collection

This thesis analyzed data from the "Motivation in mHealth Study", which utilized a mixed-methods design. The data collection took place between November 2018 to March 2020. The primary aim was to investigate what drives users of mobile health apps and wearables to share their self-collected health-related data. Additionally, the study included questions to explore the likelihood of continued use of these devices. (Henriksen, et al., 2023).

In the first phase of the motivation in mHealth study, the research team created an interview guide. The guide was based on the motivational factors identified by Locke: goals, intentions, needs, values, and emotions (Locke, 2000). These indicators for motivation were then used to identify the participants' values (knowledge and experience), needs and expectations (Woldaregay, et al., 2018). 16 in-person interviews among both males and females with and without chronic diseases were conducted. Participants were from Norway, Switzerland and Finland aged between 21-55 years and reported to be healthy, having diabetes or sickle cell disease (Woldaregay, et al., 2018). The recruitment for the interview was performed via convenience sampling but the goal was to recruit people in a diverse age range and cultural background among both males and females and with and without chronic disease status (Woldaregay, et al.,2018). The interview guide consisted of questions out of the following five themes:

1) goals, attitude and expectations, 2) wearables and sensors, 3) data sharing, 4) data integration, and 5) social media and entertainment factors

The participant's responses were then categorized via inductive thematic analysis into three sub -themes: expectations, knowledge and experience. Due to the extraction of keywords out of the interviews, the main motivational factors could be identified. On this basis the survey/ questionnaire could be developed. It included 38 questions (Henriksen, et al.,2023)

In the second phase, this survey was distributed on 9 online platforms, including several social media fora which were related to sickle cell disease and diabetes and also on general websites not related to chronic diseases. A physical distribution of the survey took place on a Swiss conference. Depending on the site were the survey was available, the announcements were in either English, French or Norwegian (Henriksen, et al.,2023). Participants answered questions anonymously regarding seven topics (Henriksen, et al.,2023):

1) background and health goal questions
2) use of wearables and sensors
3) use of mobile apps
4) data-logging
5) data sharing and data integration
6) social media and entertainment factors
7) demographic questions including chronic disease diagnostic, age and gender

Study population

Inclusion criteria

The complete data set from the “motivation in mHealth study” included all individuals who answered the questionnaire between November 2018 and March 2020. Individuals needed to be at least 18 years old and speak either English, Norwegian or French due to the three survey versions.

The inclusion criteria of ethnicity or cultural background was not further defined and people from all around the world were eligible to participate.

The study focused on the use of wearables, sensors, mobile health apps and further the willingness to share health related data. Both among healthy people and people with chronic disease. Thus, it can be assumed that familiarity with the topic played a role in the study sample.

As mentioned in the description of the data collection, the questionnaire was distributed in several ways:

Due to the online distribution, participants needed to be able to access the internet either by themselves or through friends, family members or care takers. Some of the nine online platforms were disease specific, thus participants were included according to their health status. Participants had either diabetes type I, type II or sickle cell disease (type SS or S-Beta, type SC or other) or another chronic disease that was not further specified. A distribution happened specifically among internet users in a Swiss cohort of healthy people and also in online groups of English and Norwegian diabetes patients. Information on the severity of the disease or duration of the illness was not gathered.

The selection of the study population was therefore done via convenience sampling. Further demographic information on socioeconomic status and education was not gathered in the survey. The total sample size was 814 participants who completed the questionnaire.

For this thesis, only participants who answered all the questions regarding the use of wearable devices and the importance of specific features, as well as the demographic questions on health status, age and gender were included.

In total, 584 participants were included in the study sample of this thesis.

3.2 Variables

The complete data set of the "motivation in mHealth study" included 48 variables (Henriksen, et al.,2023). In this thesis, variables regarding data login and the sharing of self-collected health data were excluded.

In total, 29 variables were included in this thesis. Six variables were only used for descriptive statistics. 17 variables were used in a binary logistic regression. Thus, several variables were included in multiple sections of the statistical analysis.

The original variables were stored as strings and have therefore been transformed into numeric variables.

Variables with demographic information included age, gender, country of origin and the health status. The variables used for descriptive statistics with the specific answer options are displayed in table 1.

3.2.1 Variables for descriptive statistics

Health status

The health status of participants was collected through the question "*Do you have a chronic disease?*" The questionnaire offered six answer options.

Participants reported to have either diabetes type I, type II, any type of sickle cell disease, any other chronic disease or not having a chronic disease. Participants could also choose do not answer this question. “Do not want to answer” was hereby treated as a missing value resulting in the exclusion of participants from the study sample.

Due to the focus of this study on how the health status may influence the uptake of wearable devices and mobile health apps, a new variable “disease_groups” was created. This variable was later re-named to “HealthStatus” as displayed in table 1.

The variable was dichotomized into Yes, having a chronic disease and No, not having a chronic disease. Hereby, all individuals answering with having any of the specific diseases as mentioned above were categorized as “Yes”. Only participants choosing the answer option “No” were categorized as “healthy”, thus added to the “No” category.

“Yes” was hereby coded as 1 and “No” as 0.

Only the dichotomized “HealthStatus” variable was used in the analysis.

For a better overview the original answer options for the question “do you have a chronic disease?” are also displayed in table 1 and can be found in the “chronic disease” column.

Age

The age of the participants was self-reported with values ranging from 18-99 years of age.

With the study focusing on how both younger and older users adopt wearable devices and mobile health apps, for the descriptive statistics a transformation of the scale variable into subgroups was performed.

The focus in the division into the three age groups was on ensuring that the group sizes were comparable as well as on similar age ranges within the groups. Therefore, participants with an age of 18 and 19 were not included in the first group for the descriptive statistics but were included in the logistic regression analysis.

The new variable “age_groups2” consisted of three age groups and was coded as follows:

1 = 20-39

2 = 40-59

3 = 60+

The variable was later re-named to AgeGroups as it is also displayed in table 1.

Gender

The gender of participants was measured using the question “what is your gender?” with “male”, “female” and “other” as answer options.

Participants identifying as “other” were excluded from the statistical analysis for this thesis due to the small number (n=32).

The variable was dichotomized and coded with Male = 0 and Female = 1

Country of origin

The country of origin was self-reported by participants using “free-text” answers.

Regular use of wearable devices and sensors

The regular use of wearable devices was measured using the question “*which of these technologies for health tracking do you regularly use?*” Participants could choose multiple of the given answer options which are presented in table 1.

Most motivating features

Features of wearable sensors resulting in participants being willing to use these over a prolonged period of time were investigated. The question “*Which features would motivate you most to use a wearable sensor longer?*” offered five multiple choice answer options.

The specific phrasing of the answer options is displayed in table 1. The header titles have been reduced. From left to right the variables are displayed as follows:

- AgeGroups
- What is your gender?
- What is your country of origin?
- Do you have a chronic disease?
- Do you have a chronic disease? HealthStatus variable
- which of these technologies for health tracking do you regularly use?
- Which features would motivate you most to use a wearable sensor longer?

Table 1: Questions with answer options for descriptive statistics variables

AgeGroups With coding	**Gender**	**Country of origin**	**Chronic disease**	**HealthStatus With coding**	**Regularly used technologies**	**Motivational features**
20-39 = 1	Male	Free text	Yes, Diabetes Type I	Yes = 1	Sensors integrated in smartphone (e.g., geolocation, accelerometer, stress tracker)	Ease of use/non-disruptive
40-59 =2	Female		Yes, Diabetes Type II/ Other	No = 0	Physical activity tracker	Relevant personalized feedback
60+ = 3	Other		Yes, Sickle Cell disease (SS, S-Beta)		Mobile health apps	Access to aggregated summarize date on population level
			Yes, Sickle Cell disease (SC/other)		Health specific measurement (e.g., glucometer/CGM/ hemoglobin meter /oximeter/spirometer/heart rate monitor)	Social integration (e.g., Facebook, Run Keeper)
			Yes, other chronic disease		Do not use any wearables or sensors	Other
			No		Other	

3.2.2 Variables for binary logistic regression

Exposure

In order to investigate whether the likelihood to adopt mobile health apps and wearables is influenced by the users' demographics and health status, three exposure variables were included in the logistic regression.
The first exposure was the health status, represented by the categorical variable "disease_group", later named "HealthStatus", with the two categories of Yes=1 and No =0. Not having a chronic disease was hereby used as the reference group.

As a second exposure, the age of participants was included in the analysis, which was measured on a scale ranging from 18-99 years of age.

Gender was included as third exposure variable, measured in the two categories of male and female. These were coded as male=0 and female=1.

Outcome

The outcome of interest was the importance of specific features of wearables and mobile health apps, that might increase the willingness to use these devices. The variables were measured on a Likert scale from 1-4, which is an ordinal measurement.

Participants rated by means of the following three questions, whether a feature was not important=1, somewhat important=2, important=3 or very important=4.

1. How important are these features for you when choosing a wearable device?
   With 6 answer options

2. How important are these specific health related features for you when choosing a wearable device?
   With 4 answer options

3. How important are these specific health related features for you when choosing a mobile health app?
   With 5 answer options

Each feature hereby represented one dependent variable which was included in a binary logistic regression model, resulting in 15 variables.

Only the Likert scale rating values 1= not important at all and 4= very important were pre-defined by the research team. The values 2 and 3 were open for interpretation.

To increase the statistical power, all 15 Likert scale variables were recoded and dichotomized with 0 = not important and 1= important. The first category "not important" hereby included all values of 1 and 2, "important" included all values of 3 and 4.

Variables for the binary logistic regression are presented in table 2.

Similar to the descriptive statistic section, the specific phrasings of the answer options are displayed in table 2. The header titles have been reduced. From left to right the variables are displayed as follows:

- What is your age?
- What is your gender?
- Do you have a chronic disease? HealthStatus variable
- How important are these features for you when choosing a wearable device?
- How important are these specific health related features for you when choosing a wearable device?
- How important are these specific health related features for you when choosing a mobile health app?

Table 2: Variables included in the binary logistic regression

Age	Gender	HealthStatus	Features of wearable devices	Specific health related features of wearable devices	Specific health related features of a mobile health app
18-99	Male	Yes	Sensor accuracy and range of values	Physical activity tracking (e.g. exercise features, heart rate/pulse tracking, fatigue, step counting, sleep tracking)	Simplicity/Usability
	Female	No	Access to several types of data (multiple sensors)	Manage disease (e.g. blood glucose, pulse, oxygen, hemoglobin)	Functionality/Features
	Other		Notification from mobile phone (e.g. detection of early signs of disease)	Predicting and preventing symptom and health deterioration"	Price
			Easy to use and quality of associated mobile app	Alerts when risky behavior/when approaching limits"	Trust/security/privacy
			Known or specific brand/price		Personalisation (tailored features)
			Ergonomic and design (e.g. physical design, battery consumption)		

3.3 Statistical analysis

3.3.1 Descriptive statistics

The statistical analysis of the data was performed in two steps. In the first step descriptive statistics were utilized to provide an overview of the demographics of the study sample. The age and gender distribution, as well as the prevalence of chronic disease are presented. Further a descriptive analysis of the regular use of tracking technologies and of the most motivating features of wearable sensors was performed. To illustrate the findings, a graphical presentation using stacked bar charts and tables was employed.

An overview of the use of wearables and mobile health devices in total (count and percent) by age group and health status is given.

In addition, the study investigated the factors that motivated participants to use these devices over a prolonged period of time. The focus lied on identifying the specific features or functionalities that were most appealing to users. For visualization purposes, clustered bar charts were used to display these finding.

3.3.2 Binary logistic regression

In the second part of the analysis, binary logistic regression models were used to investigate the importance of features of the following 3 categories:

- features of wearable devices
- specific health related features of wearable devices
- features of mobile health apps

Each of the features was displayed separately resulting in 15 variables. These represent the dependent outcome variables.

For the analysis the IBM® SPSS® statistics software package for social sciences version 28 for windows was utilized (IBM Corp., 2021).

The assumption of normality of independent variables was checked using normality plots and was met by "HealthStatus", "age" and "gender".

Absence of multicollinearity was observed via the Variance inflation Factor (VIF) and the tolerance. The models presented no correlation between the independent variable and the predictors with VIF values close to 1 (Field, 2013, p.534).

With the Durbin-Watson test the assumption of independence of observations was tested, showing results close to 2. Thus, the assumption was fulfilled (Field, 2013, p.514).

The linear relationship between the logit of the dependent variable and the predictor variables was not checked for due to the use of binary independent variables, which easily accommodates the model.

The main aim of the analysis was to determine whether the health status of participants as well as age and gender impact the adoption of these mobile health apps and wearables. Each dependent variable of a feature was included in a binary logistic regression model while first adjusting for the health status with having a chronic disease as the reference category. Afterwards, the model was adjusted for age (measured as a continous variable) and gender.

Each independent variable was added once at a time in addition to the health status in order to assess its effect on the estimate and for the prevention of overfitting.

The goodness of fit of the statistical model was assessed using Hosmer-Lemeshow tests. In all 15 models the p-value was above the significance level of 0,05, indicating that our observed event rates matched with expected event rates within our model population.

The odds ratio (OR) and 95% confidence intervals (CI) are reported after every step. Statistical significance was determined by setting the threshold for p-values at 0.05 or lower.

Sensitivity analysis

The 15 outcome variables that were included in the binary logistic regression models had been dichotomized as described in the variables section. In order to make sure that this transformation did not significantly change the end results of the analysis, a sensitivity analysis was performed. The original Likert scale measurement from 1-4 was hereby transformed as follows:

- All participants who rated a feature as "not important" were coded as 0
- All other participants (ratings from 2,3 and 4) were coded as 1 "important".

The sensitivity analysis aimed to evaluate the influence of varying values on the study's outcomes. Thus, to determine the stability and reliability of the study's findings.

3.4 Handling of missing values

Participants who didn't finish the survey or with missing values in the demographic questions on age, gender and the health status were not included in the analysis. Due to the small number of participants identifying as "other" in the gender variable (n=23), these were excluded from the sample. Further participants with missing values in questions regarding the importance of specific features, or the use of these were excluded.

Several survey questions had the answer option “don’t know”. To increase the statistical power, the answer option was recoded as “missing value” and excluded.

The final data set included 584 cases.

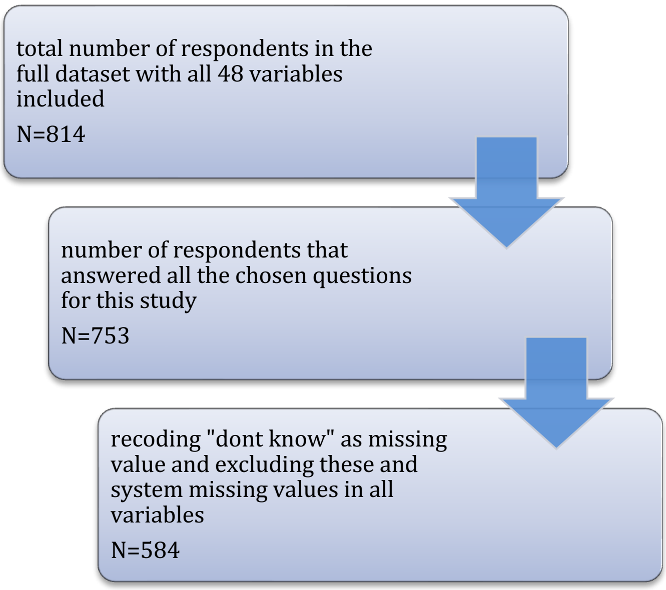


Figure 2: Flow-chart for excluded cases in the data

3.5 Ethical perspective and data storage

In 2017, before starting the motivation in mHealth study, the researchers sent a pre-application to the Regional Committee of Medical and Health Research Ethics (REK). The Committee reviewed the study approach and concluded that the project does not fall under the specification of health research and will therefore not be assessed under the Health Research act (Reference no. 2017/562/REK Nord). This was due to the projects focus on which features should be included in a mobile health app, to increase the likelihood of long-term use. The researchers did not seek to learn anything new about the participants' disease (Reference no. 2017/562/REK Nord). The Norwegian Data Protection Authority (NSD), now SIKT, received information regarding the processing of personal data (Reference no. 54558 / 3 / LB). The Project was assessed by the Data Protection Officer resulting in the permission that the project may be carried out (Reference no. 54558 / 3 / LB).

All participants gave informed consent by completing the survey. The front page of the questionnaire included this information. All data was collected anonymously and could therefore not be traced back to the participants (Henriksen, A., et al. 2022).

The original questionnaire as well as the data set was stored safely in a folder on a password secured computer and needed two-factor authentication for access.

After completion of this thesis, the dataset and all related files were deleted.

Further, in march 2023 the original data set was published on Dataverse.no and can be accessed for replication research through the following link:

Henriksen, A., Woldaregay, A. Z., Issom, D.-Z., Pfuhl, G., Sato, K., Årsand, E., Hartvigsen, G. (2023) "Replication Data for: Dataset of motivational factors for using mobile health applications and systems", https://doi.org/10.18710/AOQF05, DataverseNO, V1.

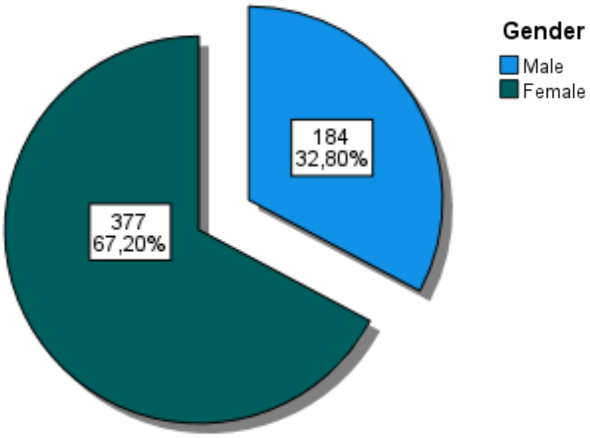
4 Results

4.1 Descriptive statistics

4.1.1 Demographics

In total 584 participant completed the survey and answered the specific questions important for this thesis.

As shown in figure 3, the majority of individuals were women (67.2%). The age distribution in this sample ranged from 18 to 99 with a mean of 45.03 (SD 19.602) Young adults represented the majority group with 44.9%. Followed by middle aged people with 32.4% and people 60 years of age and older (22.8%) as displayed in figure 4 and 5.



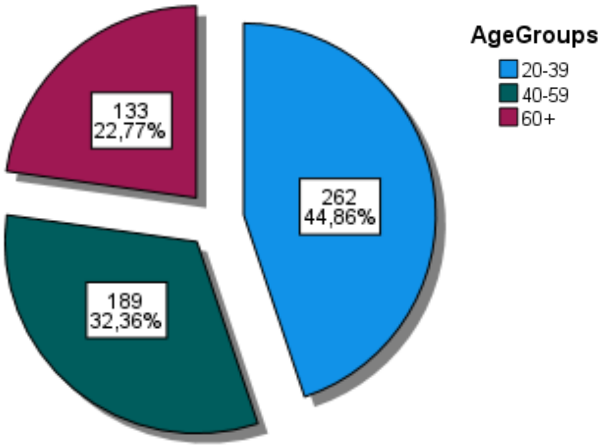


Figure 3: Gender distribution

Figure 4: Age distribution of the study population

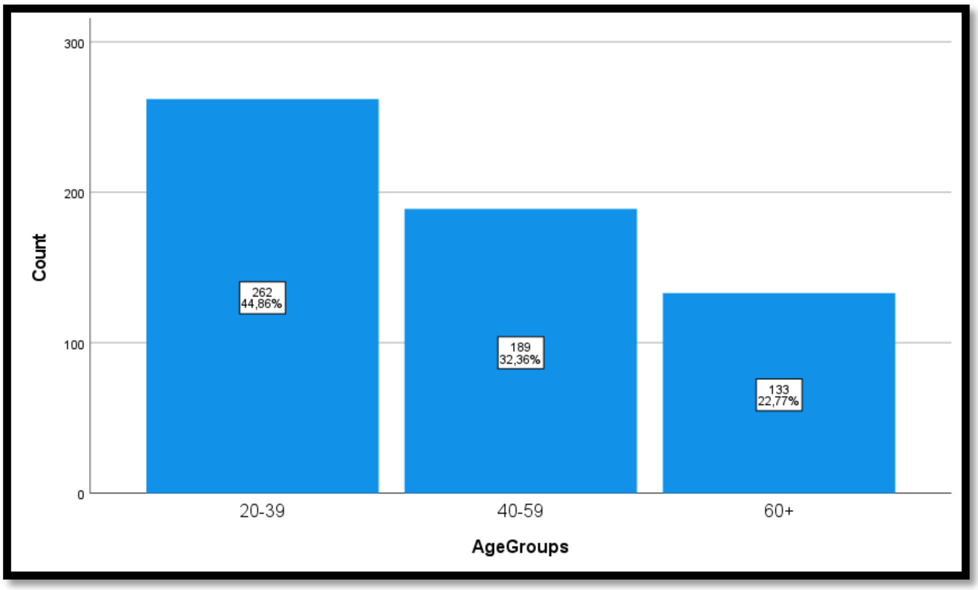


Figure 5: Visualization of the age group sizes

363 people reported to be healthy accounting for 62.2% of the sample, while 221 people answered that they have a chronic disease (37.8%). This can be seen in figure 6. People who didn't answer this question had been excluded from the sample. As shown in figure 7, the distribution of healthy people and people with chronic disease was similar within the three age groups. The majority hereby represented healthy people in each age group compared to people with chronic disease. An interesting aspect that could be seen here was that more younger people reported to have a chronic disease, than middle aged or elderly people did.

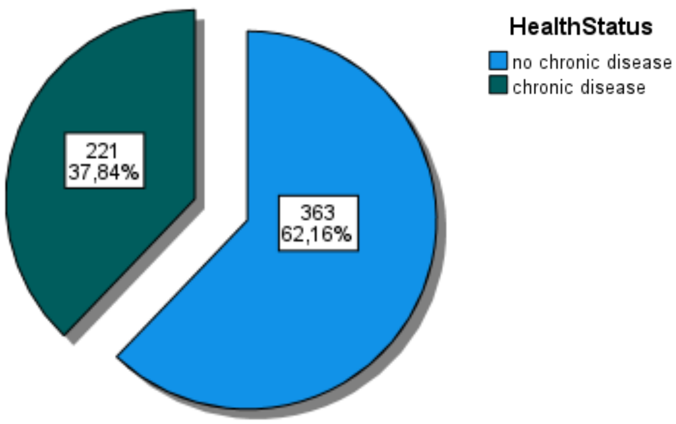


Figure 6: health status distribution

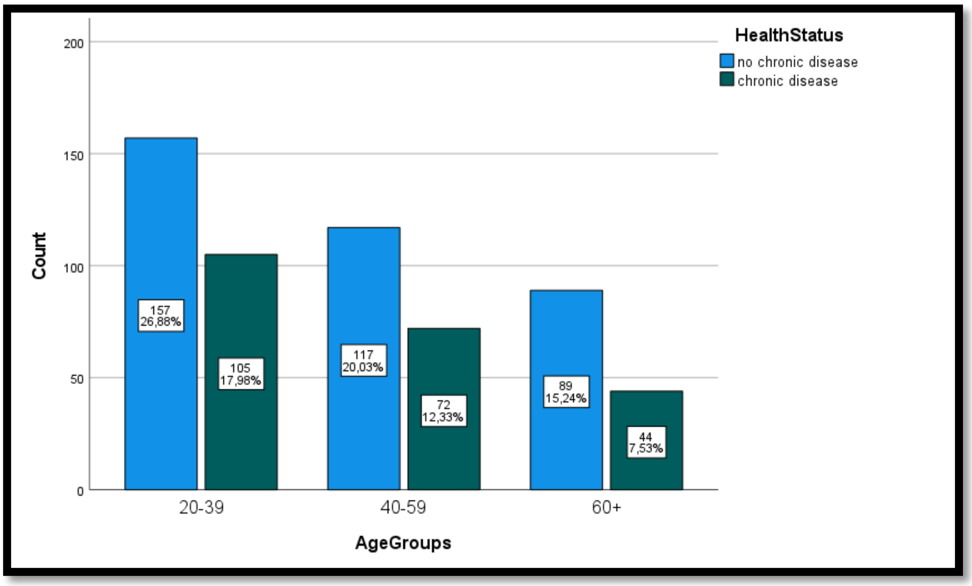


Figure 7: health status distribution within age groups

As visualized in figure 8, most participants were from the USA, Switzerland, Norway, the UK, Canada, France and Germany. Other single cases were from more than 35 countries covering all continents. The blue box which is not defined represented one participant from Korea who had answered using Korean characters which SPSS could not display.

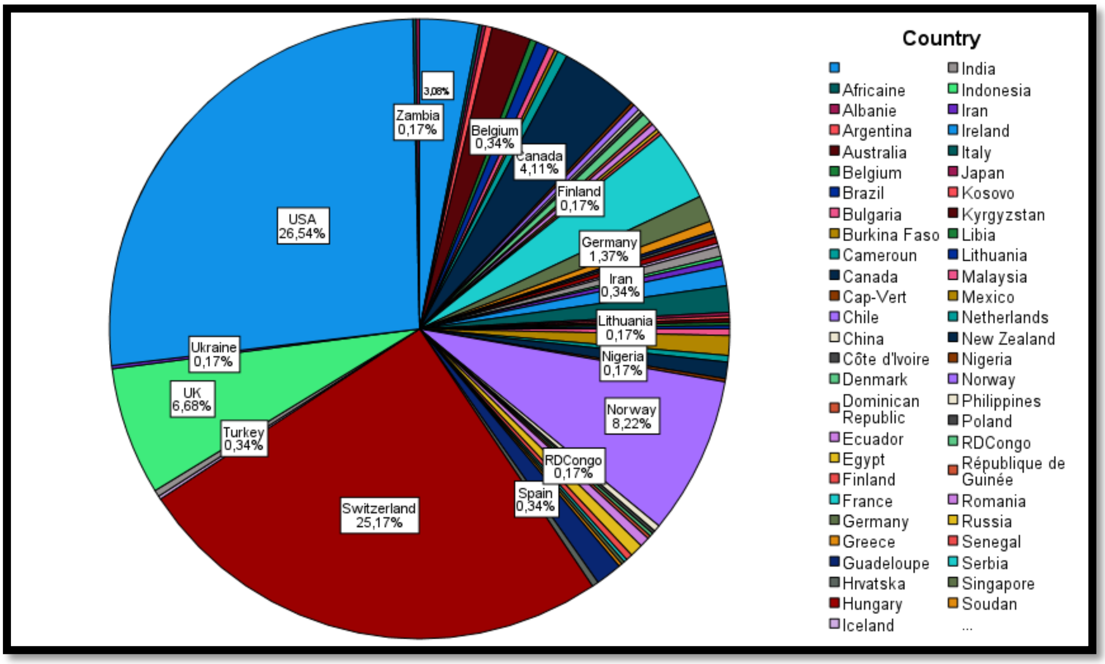


Figure 8: Countries of origin

4.1.2 Regular use of wearable devices

Participants had been asked about their regular use of wearable devices. Results are presented in total, within the age groups and according to the health status and are displayed in table 3. Most participants answered using physical activity trackers with 40.6 % of the sample. Among these people, mostly young adults between 20-39 years were represented (40.6%) followed by the middle-aged group (34.2 %). It was mostly participants without a chronic disease who regularly tracked their activity (n=140, 59.1%). Also, participants in the age group of 60 years and older used physical activity trackers more than any other device (n=60, 25.3%).

Physical activity trackers were followed by the regular use of sensors in smartphones (n=224, 38.4%). Here, too, young adults without a chronic illness were predominantly represented. The same pattern could be seen for the regular use of mobile health apps with 58% of participants being between 20-39 years old and without chronic disease (56.1%). People with a chronic disease reported to be using health specific measurements, making up 59% in this group. Also 27.2% of the sample didn't use any wearable device.

Table 3: Regular use of wearable devices within age groups and according to health status

<table>
<tr><th colspan="2"></th><th>Regular use of sensors in smartphone</th><th>Regular use of physical activity tracker</th><th>Regular use of mobile health apps</th><th>Regular use of health specific measurement</th><th>No regular use</th></tr>
<tr><td colspan="2">n of users (%)</td><td>224 (38.%)</td><td>237 (40.6%)</td><td>212 (36.3%)</td><td>161 (27.6%)</td><td>159 (27.2%)</td></tr>
<tr><td rowspan="3">Age groups</td><td>20-39</td><td>96 (42.9%)</td><td>96 (40.5%)</td><td>123 (58%)</td><td>59 (36.6%)</td><td>83 (31.7%)</td></tr>
<tr><td>40-59</td><td>72 (32.1%)</td><td>81 (34.2%)</td><td>59 (27.8%)</td><td>55 (34.2%)</td><td>47 (24.9%)</td></tr>
<tr><td>60+</td><td>56 (25%)</td><td>60 (25.3%)</td><td>30 (14.2%)</td><td>47 (29.2%)</td><td>29 (21.8%)</td></tr>
<tr><td rowspan="2">Health status</td><td>with</td><td>84 (37.5%)</td><td>97 (40.9%)</td><td>93 (43.9%)</td><td>95 (59%)</td><td>48 (30.2%)</td></tr>
<tr><td>without</td><td>140 (62.5%)</td><td>140 (59.1%)</td><td>119 (56.1%)</td><td>66 (41%)</td><td>111 (69.8%)</td></tr>
<tr><td colspan="2">Total sample</td><td colspan="5">584 (100%)</td></tr>
</table>

In Figure 9 can be seen, that for all four options of wearable devices, a minority of the total study sample reported using them.

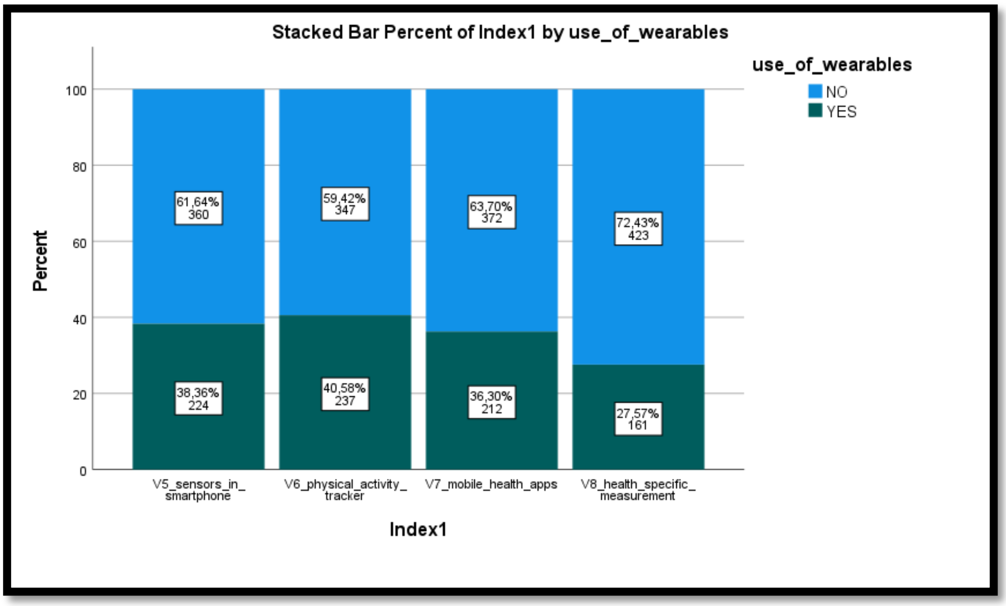


Figure 9: Overall regular use of wearable devices

4.1.3 Most motivating features for a prolonged use

Besides their regular use of devices, participants were asked about specific features, that might lead to a higher motivation for a prolonged use. The clustered bar charts (Figure 10-12) present the most relevant features according to the participants. Results are displayed by health status as well as the age group.

Among these features were the possibility for relevant personalized feedback, the access to aggregated summarize data on population level, the ease of use or a device being non-disruptive, the possibility for social integration or other.

The majority of participants reported that relevant personalized feedback would motivate them most to use a device for a prolonged period of time. In this group, the majority was between 20-39 years (21.1%). The second highest rated feature was the ease of use. Also, here mostly young adults rated this as very important (16.3%) in comparison to middle-aged people (13.7%) and older adults (8.3%). Access to aggregated data and social integration did not seem very motivating for a prolonged use (Figure 10).

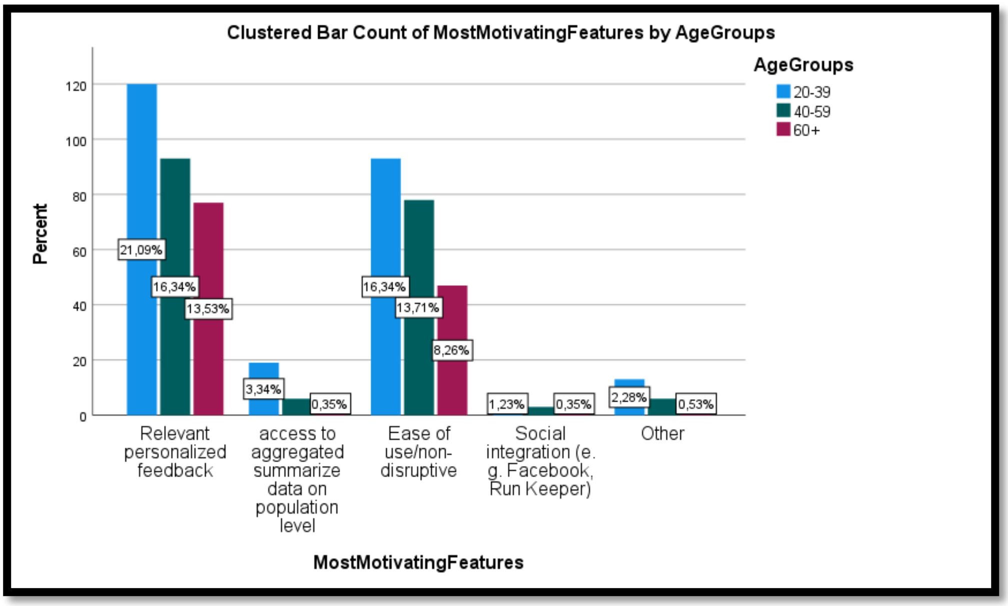


Figure 10: Most motivating features for a prolonged use within age groups

Comparing these features among the groups of healthy participants and people with chronic disease, the same pattern of choice could be seen (Figure 11).

Both groups preferred relevant personalized feedback and ease of use over the other features. In the group of healthy people, 34.3% chose relevant personalized feedback and 21.4% chose the ease of use. In comparison, around 16.7% of participants with chronic disease chose the same features as most important for a longer use of the devices.

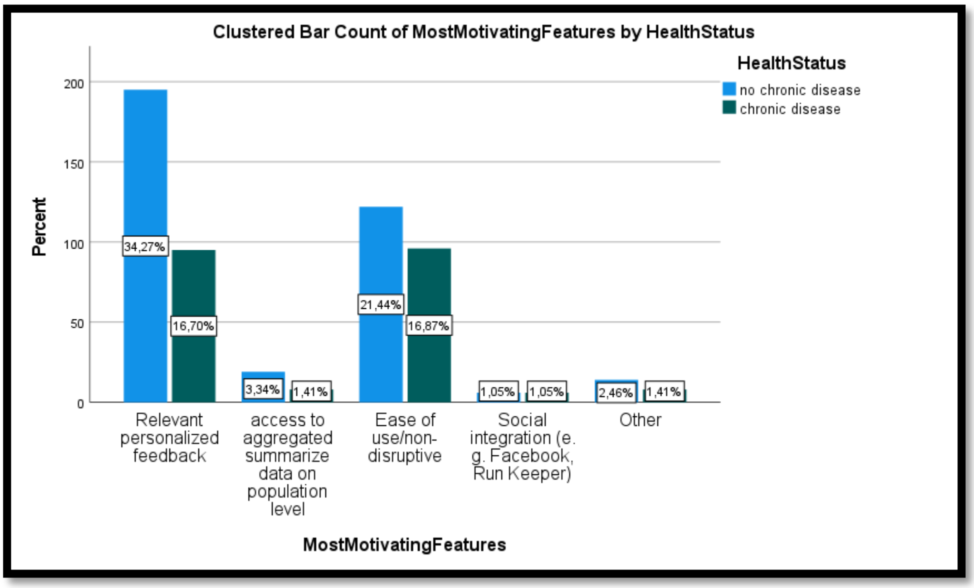


Figure 11: Most motivating features for a prolonged use within the health status

Figure 12 shows, that both in all three age groups as well as among people with chronic disease and healthy people, the two mentioned features of relevant personalized feedback and ease of use significantly stick out for a prolonged use of wearable devices.

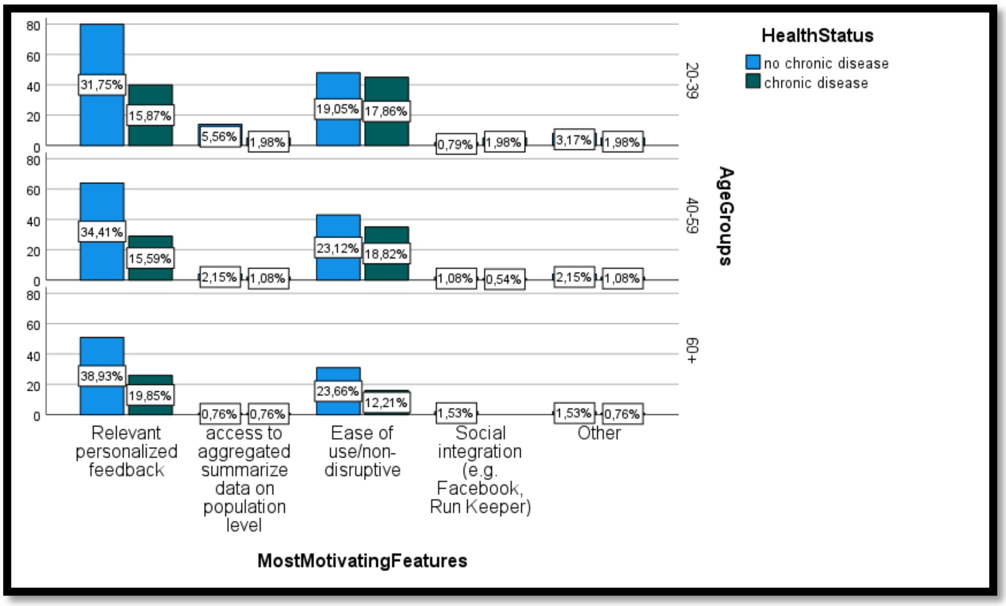


Figure 12: Most motivating features for a prolonged use within age groups and health status

4.2 Binary logistic regression

4.2.1 Wearable devices

Table 4 shows the effect estimates for the importance of six features integrated in wearable devices. In the first column odds ratios with 95% confidence intervals are presented after adjusting for the health status. Having a chronic disease was hereby used as the reference group. In column two and three, the odds ratios and 95% CIs after adjusting for health status and age, and after including gender into the model are displayed.

Among the six features only the importance of notifications of mobile phones seemed to be significantly influenced by having a chronic disease and age with a p-value of 0.011 (OR, 1.6 95% CI 1.11-2.3).

The point estimates for sensor accuracy and range of values as well as ergonomic and design indicated a positive association between the importance and having a disease. Due to Confidence intervals crossing one, the results carry some uncertainty (OR 1.29, 95% CI 0.70-2.36 and OR 1.35, 95% CI 0.91 – 2.02).

The importance of an access of several types of data, ease of use and the quality of the app as well as a known or specific brand or price showed inconclusive associations in our sample.

Table 4: Logistic regression model results for features in wearable devices

Outcome: Importance of…	Exposure: Chronic disease OR (95% CI)	+Age OR (95% CI)	+Gender OR (95%CI)
Sensor accuracy and range of values	1.29 (0.71-2.37)	1.29 (0.71-2.38)	1.29 (0.70-2.36)
Access of several types of data	0.75 (0.51 – 1.10)	0.75 (0.51 – 1.10)	0.75 (0.51 – 1.11)
Notifications of mobile phone	1.57(1.09-2.23)	1.58 (1.11-2.26)	1.58 (1.11-2.26)
Ease of use and quality of mobile app	0.94 (0.55 – 1.62)	0.94 (0.55-1.62)	0.94 (0.54-1.61)
Known/specific brand or price	0.75 (0.53 – 1.08)	0.76(0.53-1.08)	0.75 (0.52 – 1.08)
Ergonomic and design	1.36 (0.92 – 2.00)	1.36 (0.91-2.02)	1.35 (0.91 – 2.02)

4.2.2 Specific health related features

Further, the importance of four specific health related features of wearable devices was investigated (Table 5).

For the importance of physical activity tracking a negative trend in the odds ratio could be observed, while the confidence intervals (CIs) also narrowed down slightly in each iteration. This negative association was significant with a p-value below 0.001 (OR 0.46, 95% CI 0.29-0.71).

Having a chronic disease was associated with 2.417 times higher odds of perceiving the importance of managing the disease compared to individuals without a chronic disease (OR 2.42, 95% CI 1.62 – 3.61).

For individuals with a chronic disease, the analysis suggested a modest increase in importance of predicting and preventing health deterioration (OR 1.43, 95% CI 0.91 – 2.25). It is important to note that the variable showed a high number of missing cases (n=218), resulting in a smaller sample (n=366) for this regression analysis.

A similar positive association between chronic disease and the importance of the outcome variable could be seen for alerts of risky behavior (OR 1.32, 95% CI 0.89– 1.94). Again, it was not possible to conclude that there is sufficient evidence for this trend, due to a p-value > 0.05.

Table 5: Logistic regression model results for specific health related features in wearable devices

Outcome: Importance of…	**Exposure: Chronic disease OR (95% CI)**	**Age OR (95% CI)**	**Gender OR (95%CI)**
Physical activity tracking	0.46 (0.29 – 0.72)	0.46 (0.29-0.71)	0.46 (0.29 – 0.71)
Manage disease	2.40 (1.60 – 3.57)	2.40 (1.61-3.59)	2.42 (1.62 – 3.61)
Predicting and preventing health deterioration	1.49 (0.96 – 2.33)	1.42 (0.91-2.23)	1.43 (0.91 – 2.25)
Alerts of risky behavior or reaching of limits	1.31 (0.89 – 1.93)	1.31 (0.89-1.93)	1.32 (0.89– 1.94)

4.2.3 Mobile health apps

Additionally, the importance of five specific health related features in mobile health apps was analyzed, as presented in Table 6.

Within the category of features for mobile health apps, the logistic regression analysis revealed a statistically significant and negative association between having a chronic disease, age, gender, and the importance of trust, security, and privacy (p=0.038).

Having a chronic disease was hereby associated with 0.626 times lower odds of perceiving the importance of trust, security, and privacy compared to individuals without a chronic disease (OR 0.626, 95% CI 0.40-0.97).

The point estimate for the importance of personalization and tailored features indicated a positive association between people with chronic diseases, age and gender (OR 1.05, 95% CI 0.71-1.56). With a p-value above the 0.05 significance-level, the result showed insufficient evidence to conclude on that association. Inconclusive associations could also be observed for the importance of simplicity and usability, functionality features and the price of a mobile health app.

Table 6: Logistic regression model results for features in mobile health apps

Outcome: Importance of…	Exposure: Chronic disease OR (95% CI)	Age OR (95% CI)	Gender OR (95%CI)
Simplicity and usability	0.89 (0.49– 1.65)	0.89 (0.49-1.65)	0.89 (0.49 – 1.64)
Functionality features	0.66 (0.40 – 1.09)	0.66 (0.40-1.09)	0.66 (0.40 – 1.09)
Price	0.79 (0.53 – 1.19)	0.78 (0.52-1.18)	0.78 (0.51 – 1.17)
Trust, security, privacy	0.62 (0.40 – 0.97)	0.63 (0.41-0.97)	0.63 (0.40 – 0.97)
Personalization/tailored features	1.06 (0.71 – 1.56)	1.06 (0.71– 1.56)	1.05(0.71 – 1.56)

The results of the sensitivity analysis showed no significant difference compared to the binary logistic regression performed with the dichotomized variables. the conclusions remained consistent across different conditions, thus providing insights into the robustness of the results.

5 Discussion

5.1 Summary of main findings

The primary aim of this study was the identification of motivational drivers of both healthy users and people affected by chronic diseases, that have the potential to increase and prolong the usage and adaption of mHealth applications, wearables and trackers.

Results from the descriptive statistics part of this study showed that features such as relevant personalized feedback and the ease of use in devices represented the most motivating features for a prolonged use. This trend was evident for all age groups as well as people with and without chronic disease.

An additional focus lied on examining the impact of users' demographics (age and gender) and health status on their adoption of mobile health apps and wearables.

With the logistic regression analysis, it was possible to demonstrate that there might indeed be some significant differences in what people with chronic disease find important compared to healthy people. Among the investigated features for wearable devices, notifications on mobile phones represented an important feature for chronic disease patients. The features of sensor accuracy and range of values as well as ergonomic and design indicated a positive association between the importance and having a chronic disease. Nevertheless, the statistical power had been too low for a valid conclusion. An investigation within a bigger sample size might lead to stronger results.

Within the category of specific health related features for wearable devices, the analysis revealed the following: Individuals with a chronic disease tended to perceive a lower importance of tracking their physical activity, than healthy people. After accounting for age and gender, the negative association implied that especially younger people might find this feature crucial and be more likely to recognize and prioritize the importance of monitoring their physical activity levels in comparison to older adults.

As expected, results for the ability to manage a disease with a wearable device showed that individuals with a chronic disease are more likely to prioritize and recognize the significance of managing their condition effectively.

A similar positive association would have been expected for the feature of predicting and preventing health deterioration. Nevertheless, results implied that there was insufficient evidence to conclude that having a chronic disease significantly influences the importance placed on this feature. This result might have been influenced by the high number of missing cases (n=218), which resulted in a smaller sample (n=366) for this regression analysis. Repeating this analysis with a bigger sample size might provide further evidence.

Within the category of features for mobile health apps, the logistic regression analysis revealed that individuals with a chronic disease tend to place less importance on trust, security, and privacy concerns than healthy people. Also, a positive association for the importance of personalization and tailored features could be seen, but results were inconclusive.

To summarize, this study was able to identify important motivational drivers of both individuals with and without chronic disease that might prolong the usage and adaption of mHealth wearables and applications. Further, some interesting findings could be observed, that a users' demographics might indeed impact their adoption of mobile health apps and wearables. Nevertheless, the validity of the results needs to be treated with caution due to inconclusive results within the analysis.

5.2 Reflection on findings

The research field which is devoted to investigating user experiences and needs in mHealth plays an important part in how these tools can be accessed and utilized.

This master's thesis is context-dependent and of relative significance, yet it can offer valuable insights into the motivational factors that might contribute to an enhanced user-engagement. Understanding patterns in users' preferences for mHealth devices is crucial. Gaining knowledge on how age or having a chronic disease might influence the adoption of the devices can play an important part in future development (Vo, Auroy & Sarradon-Eck, 2019; Jaana & Paré, 2020).

According to Jung et al. the most relevant and prominent shortcomings of current mHealth applications in regards to diabetes include the following: deficiencies in user-friendly and easily interpretable reports, effective communication capabilities, as well as information feedback (Jung et al., 2016). Our results were consistent with this study, with ease of use and relevant personalized feedback representing the most motivating key features.

A study by Scheibe et al. investigated which factors of mHealth apps would lead to a higher acceptance by middle aged (50+) diabetes patients. Their findings showed similar trends that ease of use and individually tailored features might have a positive effect on the encouragement to use these devices (Scheibe et al., 2015). The importance of notifications as well as a positive influence of the apps' design and sensor accuracy on a long-term user engagement could be highlighted by Vaghefi et al.:

Their results of a longitudinal study on a continued use of mobile health apps from 2019 marked notifications like text reminders or alerts as one key factor for a prolonged use. Further, the accuracy of data and a simple and clean interface design seemed to matter to a high number of users (Vaghefi, et al., 2019). These outcomes align with our analysis, demonstrating consistency in the results.

Our analysis gave insights that especially the ability to manage a disease with mHealth applications was within the user preferences. Both, research by Mendiola et al., as well as Vo et al. could support these findings (Mendiola et al., 2015; Vo, Auroy & Sarradon-Eck, 2019). The observation that physical activity tracking was not a highly rated feature in our analysis, might be able to be explained. According to Mendiola et al, the execution of this feature might play an important role on the user engagement (Mendiola et al., 2015). Further, the importance of closely tailored and personalized features could be observed in our regression analysis. These results were in line with the gained insights of Mendiola et al. and Vo et al. (Mendiola et al., 2015; Vo, Auroy & Sarradon-Eck, 2019). Despite the fact that some of our findings showed inconclusive results, a consistent pattern could be demonstrated. The results we gained within the study sample showed an alignment with observations of other researchers and might contribute to the further understanding of user preferences in mHealth.

5.3 Methodological considerations

5.3.1 Strengths and limitations

When research is performed, it is crucial to reflect on the chosen methods and the strengths and weaknesses that might influence the final result interpretation. Thus, a critical appraisal on the central methodological aspects of this thesis is given.

Research Design:

A descriptive cross-sectional study design was used due to the data that was collected at a single point in time, focusing on individual preferences of participants. The goal of this thesis was to describe the key motivational factors in mobile Health usage within the specific study population. The relationship between a variety of exposure and outcome variables was hereby investigated. By using this study design, variations within the preferences of the study population according to age, gender, and health status could be examined. It allowed the identification of potential associations between the chosen variables. These might help to generate hypothesis for future research (Wang & Cheng, 2020, pp.65-66). Another strength of a cross-sectional study design is the ability to prevent ethical difficulties (Wang & Cheng, 2020, p. 67). Nevertheless, it is crucial to mention important limitations of this research method. Even though we might have gained valuable insight on the relationships between user preferences and how these might be affected by age or health status, it is not possible to conclude on any causality (Wang & Cheng, 2020, p.67).

Data Collection:

The data on which this thesis is based was collected via online questionnaires. These were based on in-person interviews with individuals who shared similar characteristics to the study population. Questionnaire based research has the advantage to reach larger and more diverse populations globally, or to target a specific defined population (Dewaele, 2018, p.271). The distribution of the questionnaire happened on disease specific online fora as well as more general websites. Thus, the study population was collected via convenience sampling. This could make sure that participants fulfill the inclusion criteria for the target population (Henriksen et al., 2023). As could be seen in the description of the demographic aspects of the sample, the group sizes of all three age groups were similar, allowing for a comparison. Further, participants were from countries all around the globe, showing diversity within the study sample. The heritage of participants might have been a factor that affected the age groups sizes. Sickle cell disease still has a quite low life expectancy and the access to health care services is not the same all around the globe (WHO, 2022a; American Society of Hematology, 2023). But we did not gain any further information on where participants lived, only on the country of origin. We also had no insight on how far chronic diseases had progressed, since this was not the focus of this study.

An additional benefit of this approach is the promotion of anonymity and honesty in responding. Online questionnaires avoid a direct researcher-participant interaction, which reduces the pressure to participate. This resulted in a lower likelihood of participants exaggerating or manipulating their answers. (Dewaele, 2018, p.271).

The Interview questions were out of five themes that were relevant to the study objectives (Henriksen et al., 2023). This allowed the researchers to gain a deep understanding of participants' perspectives, experiences, and concerns and thus gaining real-world insight. This process could ensure that data is collected that aligns with the specific research aim (Nayak, & Narayan, 2019, p. 31). Nevertheless, it is important to mention that self-developed questionnaires bear weaknesses. Questions and items need to be formulated clear and concisely, achieving a balance between completeness and comprehensiveness, while also considering the overall length of the questionnaire. Thus, important areas of the broad topic of mobile health might have not been covered in this study (Dewaele, 2018, p.270). Also, the question regarding the regular use of wearables and mobile health apps was formulated in a more general way and did not include specific information on which health related devices were used by participants. This might affect the data quality in this study (Henriksen, et al., 2023).

The utilization of questionnaires as a systematic data collection tool enabled the gathering of valid and reliable data (Dewaele, 2018, p.269). A weakness here is that we did not have information on which specific online websites the questionnaire had been distributed. Further, no information on the response rate was available. In assessing relationships between various variables, an adequate sample size is crucial to achieve a precise and reliable outcome. Although age and health status may have had an actual impact on the outcome variable, the study lacked sufficient statistical power to detect it. The sample size of 584 participants allowed for an analysis that could display several positive relationships. An even larger sample size would have likely produced more robust results compared to those obtained in this master's thesis project. Consequently, caution should be exercised when interpreting the findings of this study.

According to Lefever et al., online surveys offer both advantages and limitations in regards of response rates: Participants have the flexibility to engage at their preferred time and location, as long as they have internet access and a computer. This freedom of choice can be advantageous, as respondents willingly decide when to respond to the questions. However, it can also be a drawback if participants delay completing the questionnaire, and unintentionally forget about it (Lefever, et al., 2007, pp. 575-576). According to Dewaele, another negative aspect could be the possibility of participants answering the questions at random or not answering at all (Dewaele, 2018, p. 271). It is likely to say that an interest or experience in the topic of mobile Health might have influenced the willingness of people to participate in this study (Dewaele, 2018, p.273). This might have led to more younger people participating than middle aged or elderly adults, as could be seen in the demographic results.

Data Analysis:

In order to provide a concise summary of the main demographic characteristics of the study sample as well as the overall use of wearable devices and mobile health applications, descriptive statistic methods were utilized. Using the same method for the exploration of which features motivate participants most to prolong their use of the devices, trends and patterns could be displayed. Further, a visualization of the data was possible (May, 2017).

In the second part of the analysis, binary logistic regression was performed with the aim to investigate the association between the importance of a feature and age, chronic disease and gender. Specifically, binary logistic regression analysis was chosen due to the dichotomization of the Likert scale variables. Regression techniques have the advantage that they are highly adaptable as they facilitate the assessment of associations, outcome prediction, and the control of confounding variables. Binary logistic regression, as a specific technique, offers efficiency and robustness in examining the impact of a set of independent variables on a binary outcome. It quantifies the individual contribution of each independent variable, providing valuable insights into the relationship between the predictors and the outcome (Stoltzfus, 2011, p.1099). Also, the logistic regression models had been tested for the required assumptions and met these.

The dichotomization of the Likert scale variables was decided in order to adjust for the undefined Likert scale rating options. These variables are ordinal, thus parametric statistics measures should normally not be applied. This represents a limitation due to the simplification of the data and a reduction in information (Norman, 2010, pp.627-628). It can still be highlighted that according to the literature, under special circumstances, this decision is valid (Norman, 2010, p. 631).

Potential drawbacks were accounted for via a sensitivity analysis, which showed no significantly different results. Nevertheless, it is crucial to mention that this decision might have led to a decrease in statistical power in our analysis (Norman, 2010, p.628).

Risk of bias

The design of this study was susceptible to several types of biases that need consideration. Bias in a study refers to systematic errors that occur and lead to an inaccurate estimation of the actual impact of an exposure on the desired outcome. It introduces deviations from the truth and can skew the findings in a particular direction (Wang & Cheng, 2020, p. 68). Due to the method of using online questionnaires, participants were selected according to their interest and willingness. This self-selection bias represents a crucial but inevitable limitation (Dewaele, 2018, p. 271). Having difficulties in accessing the technology required for participation in this study might have disproportionately affected older individuals. Further, older individuals who choose to participate may have had distinct motivations or preferences compared to non-participants. This selection bias can impact the generalizability of the findings to the broader older population (Mayeda, et al., 2020). Due to the data being self-reported, a risk for recall-bias and information bias might also be prevalent in this study (Jager, et al., 2019, p. 439).

Generalizability

Due to the existing types of bias in this study, missing information and mentioned limitations, the external validity as well as generalizability of the results are likely to be compromised. The gained insights on user preferences of mHealth applications according to age and health status could not be based on adequate statistical power. Thus, these might only be applicable for the specific study population and are not representative on a broader scale. A replication of the study in a different setting or sample might provide further evidence on the generalizability of the findings.

5.3.2 Future implications

In the realm of healthcare, advancements have consistently been marked by innovations in technology. The future of mHealth holds tremendous potential to transform healthcare delivery. Technological innovations, such as wearable devices or smartphone applications are poised to enhance the accessibility, efficiency, and quality of healthcare services (WHO, 2011). Further research and development in mobile health technologies are essential to unlock their full potential, enabling personalized and patient-centered care. User-centered design is paramount in the development of effective and engaging mobile health interventions. Future research should focus on further understanding user preferences, needs, and experiences to create personalized and user-friendly mHealth solutions. By adopting a user-centric approach, mHealth interventions can promote increased engagement, adherence, and sustained behavior change (Borrelli, & Ritterband, 2015, pp.1205-1206).

Data privacy and security are critical considerations in the implementation of mobile health. As the collection and sharing of sensitive health information increase, robust data privacy and security measures must be prioritized (Williams & Maeder, 2015). Further research is needed to develop and evaluate privacy-preserving technologies, data encryption methods, and secure data sharing frameworks. Building trust among users and healthcare providers is paramount to foster the widespread adoption of mHealth. Collaboration between researchers, technology developers, policymakers, and regulatory bodies is crucial to establish ethical and legal guidelines that protect patient privacy while facilitating data sharing for research and healthcare purposes (WHO, 2011; Williams & Maeder, 2015; WHO, 2019)

The integration of mobile health technologies with existing healthcare systems and workflows presents both opportunities and challenges. Interoperability, data integration, and healthcare provider acceptance are key considerations for successful integration (WHO, 2019). Research should explore strategies to seamlessly incorporate mHealth solutions into clinical practice, ensuring that they align with established healthcare processes (WHO, 2019).

Finally, addressing health disparities and ensuring equitable access to mHealth interventions is of utmost importance. Future research should focus on reducing disparities in access to technology, digital literacy, and healthcare resources. Targeted interventions should be developed to cater to the needs of marginalized populations, individuals with limited resources, and those residing in underserved areas. Collaboration between researchers, policymakers, and community organizations can help bridge the digital divide and promote equitable access to mHealth technologies, thus reducing health disparities and improving health outcomes all over the globe (WHO, 2019).

6 Conclusion

The main aim of this thesis was to identify the motivational drivers of both healthy users and individuals affected by chronic diseases that may increase and prolong the usage and adaption of mHealth applications, wearables, and trackers. Additionally, a further focus was placed on examining the impact of users' demographics (age and gender) and health status on their adoption of mobile health apps and wearables.

By examining the specific factors that motivate different age groups and individuals with varying health conditions, valuable insights were gained into how to design and tailor mobile health interventions to enhance long-term engagement and adherence. Relevant personalized feedback and the ease of use represented key motivators.

Through an analysis of the relationship between demographic factors, as well as considering the health status, a comprehensive understanding was obtained of how these factors interact and potentially influence the adoption behavior of users. Several positive influences could hereby be observed: Mobile notifications, the design/interface, sensor accuracy, tailored features and most outstanding, managing a condition were rated as highly important.

In summary, this study offered valuable understanding regarding the motivational factors and usage trends of mobile health apps and wearables among both young and elderly individuals with and without chronic illnesses. However, additional research is necessary to enhance external validity and consider the specific characteristics of the sample on which this study was conducted.

Nevertheless, the findings from this study make a valuable contribution to the existing body of knowledge in the field of mobile health. They provide actionable insights for developing interventions and strategies that effectively cater to the diverse needs and preferences of various user groups.

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