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Health Information Behavior of Activity Tracking Technologies Users

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I never thought I would be standing here.
Almost four years of hard work are over now. Those years were surrounded by self-doubt, challenges but most importantly it was a journey of progress, getting mature and acknowledging all the experiences and insights these four years brought.
Now, I know and understand why most researchers are saying 'a well-done thesis is a done thesis.'

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Thank you.
Aylin Ilhan

Contents

List of Abbreviations

ATT	Activity Tracking Techonology
GDPR	General Data Protection Regulation
GPS	Global Positioning System
HIB	Health Information Behavior
HIL	Health Information Literacy
HCI	Human-Computer Interaction
HII	Human-Information Interaction
ICT	Information and Communication Technology
IB	Information Behavior
IL	Information Literacy
ISE	Information Service Evaluation
IS	Information System
IQR	Interquartile Range
PIS	Personal Informatics System
RQ	Research Question
SDT	Self Determination Theory
SNS	Social Networking Serivce
TAM	Technology Acceptance Model
TAM2	Technology Acceptance Model 2
TK	Techniker Krankenkasse
U&GT	Uses and Gratifications Theory
UTAUT	Unified Theory of Acceptance and Use of Technology
WAT	Wearable Activity Tracker

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1 Introduction

Dealing with information, knowledge and digital documents
is one of the most important skills for people in the 21st century.
(Stock & Stock, 2015, p. vii)

The 21st century's society is encompassed by an everyday information explosion. Information and Communications Technologies (ICTs) have all the makings of offering information anytime and anywhere. Starting from information retrieval systems (e.g., Google) up to Social Media Platforms, information is omnipresent. Thereby it seems that the responsibility to scrutinize the quality of that information lies in the population's responsibility.

> "One central element of our contemporary world is the explosive growth of information coupled with the ready access instantiated in the Internet. Individuals have free access to an often bewildering wealth of information" (Johnson & Case, 2012, p. 5).

An intent look to social media platforms confirms that companies counteract misinformation dissemination, but there is always room for improvement. People are faced with the challenges to seek, find, assess, and use information every day. Dealing with information is characterized as an inevitable skill by Stock and Stock (2015). The Information Science discipline continued investigating users' Information Behavior (IB) for decades. The focus on information, especially how users are applying information, relates to IB, which is a core aspect of information science. IBs research is "particularly concerned with the interactions between information user (with or without an intermediary) and computer-based information systems, of which information retrieval systems for textual data may be seen as one type" (Wilson, 1999, p. 263). Indeed with emerging technologies, the IB itself becomes so heterogeneous and diversified, it requires a broader conceptualization of IB (e.g., Scheibe, Fietkiewicz, & Stock, 2016; F. Zimmer, Scheibe, & Stock, 2018). With changing sources of information and everyday-tasks the information needs to be altered as well. In the moment where an individual is realizing that there exists a knowledge gap to continue or start doing something - there exists an information need (Case & Given, 2016).

How is IB characterizable? Wilson (2000, p. 49) explains information behavior as a subset of human behavior. "Information Behavior is the totality of human behavior in relation to sources and channels of information, including both active and passive information seeking, and information use" (Wilson, 2000, p. 49). Further, "a conscious effort to acquire information in response to a need or gap in your knowledge" is assigned to information-seeking behavior which is a subconcept of Information Behavior (Case & Given, 2016, p. 6). "Understanding how individuals seek and use information has long been a central focus of information science" (Dalrymple & Zach, 2015, p. 210).

With this in mind, it is even more interesting how new technologies create new challenges and opportunities. More particularly, the access to health-related information by ICTs in everyday life has been increasing for some years. There are many social media sources to consume health and fitness-related information from, and there are evermore self-tracking technologies offering health and fitness-related information about oneself. According to Johnson and Case (2012, p. 4), "individuals are being empowered to find the answers they need to solve their problems, in part through the explosive growth of health information technology." A new realm of ICT arose the past years. IDC (2020) reported, even though hearables captured the most wearable device growth in the fourth quarter of 2019, categories such as watches and wrist bands showed a year-over-year growth as well. For example, "Xiaomi ranked second shipping 12.8 million wearables of which 73.3% (9.4 million) were wristband" (IDC, 2020). Even though those wearables offer health and fitness-related information 24/7 they are not declared as health technology.

From an information science perspective, especially considering the information behavior, activity tracking technologies introduce a new research area. Critical questions arise such as, which skills are required to use and assess that information? Which aspects influence users to use and share information about their data on social media platforms? How can information science create an added value besides the content of information?

This thesis aims at answering information science-related questions to reveal the information science's unique characteristics, especially regarding the core component – information. Apart from the fact that information science is interrelated with other disciplines, information itself plays a crucial role within information science and makes this discipline unique. According to Stock and Stock (2015, p. 8), "[t]he fixed point of information science is information itself, i.e. the structured information content which expresses knowledge." Activity Tracking Technologies (ATTs) empower users to gain awareness about their behavior, gain knowledge through the tracked data. There is a considerable potential as ATTs collects manifold information, which can, respectively, from an information science perspective, improve users' knowledge if they are represented in a structured manner.

First of all, the terms related to ATTs will be defined. Currently, there are different ATTs in the market. Starting from smartwatches such as the Apple Watch up to mobile applications such as Strava or MyFitnessPal. Therefore, in this thesis, I understand Smartwatches (e.g., Apple Watch, Samsung Gear, Fossil, Fitbit Versa), fitness trackers (Fitbit Charge, Xiaomi, Garmin) and health and fitness-related mobile applications (e.g., Strava, MyFitnessPal, Runtastic) as ATTs. Until now, apart from the term self-tracking, there are further similar terms being used. These terms are "lifelogging, personal informatics, personal analytics, and the quantified self" (Lupton, 2016, p. 2). In recent years, companies such as Fitbit, Garmin, and Xiaomi, manufactured Wearable Activity Trackers (WATs) which are intended to enable users to digitally self-track their health and fitness-related behavior. They promote those ATTs with claims such as "...these trackers were made to help you live a healthier life" (Fitbit, 2020) or "It keeps you more informed and encourages better habits" (Apple, 2020). The critical question arises: Do not users need skills to be able to use those information extensively? For example, according to Johnson and Case (2012, p. 9) "an individual's level of health literacy

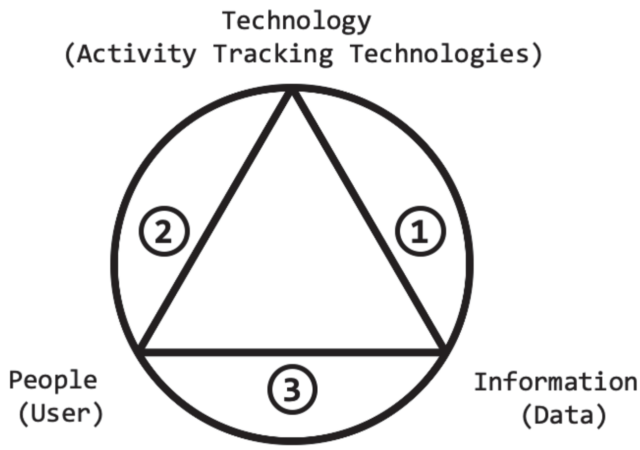

Figure 1.1: Interaction of components Information, Technology and Users, adapted from (Shin et al., 2019, p. 11)

determines the information base they start with when confronting a health problem; their literacy determines their need for information and what should be sought."

The main goal of this thesis is to shed light on the research domain of activity tracking technologies from an information science perspective by drawing on the conceptual triad (see Figure 1.1).

Shin et al. (2019) conceptualized a triangle that characterizes the complex interplay between users, the technology (self-tracking wearables), and the content (information). While researchers concentrated intensely on the technology and medical settings, including patient's treatment, the axes (3) "Information Data and People (Users)" and (2) "People (Users) and Technology" are less investigated (Shin et al., 2019). In their literature review they investigated articles from 2017–2019 on WATs. Shin et al. (2019) emphazise that information science plays a crucial role, especially regarding "data-centric research" that refers to the axis (3) *People (User) and Information(Data)*. The data-centric research needs to be investigated more deeply, as this axis also reflects the need of users (Shin et al., 2019). Ilhan, Feng, Fietkiewicz, and Eikey (2020, p. 2) similarly stress "that information science community is well-positioned to study self-tracking from a more holistic perspective with more emphasis on the role of information." Pingo and Narayan (2018, p. 506) also highlight that "[t]he understanding of how people make meaning out of fitness tracker data is a vital aspect of their information seeking, which provides an important and interesting perspective for information behaviour research."

From an information science perspective, users of Information Systems (ISs) have a need that regularly leads to an information need. Besides the information and the information content, the usability of a system that provides these information is crucial. According to Wilson (2000, p. 50), the so-called "Information Use Behavior" does not contain the sole use of such information but rather "incorporating the information found into the person's existing knowledge base" (Wilson, 2000, p. 50). Wilson (2000, p. 50) further explained that information use behavior "may involve, therefore physical acts such as marking sections in a text to note their importance or significance, as well as mental acts that involve, for example, comparison of new information with existing knowledge." Bates (2010) explained that "'Information behavior' is the currently preferred term used to describe the many ways in which human beings interact with information, in particular, the ways in which people seek and utilize information" (Bates, 2010, §1-2).

A study by Scheibe et al. (2016) already accents that information behavior is both narrowly and broadly defined in the information science domain. This thesis follows the notion of Scheibe et al. (2016, p. 9) that information behavior "covers all human information-related activities", which is in line with the definition by Wilson (2000). This enables a holistic view of the subject of ATTs from an information science perspective.

The proposed IB model by F. Zimmer et al. (2018) emphasizes different aspects that can influence human information behavior and is, therefore, in line with the broader definition of IB. In their model, they investigated aspects such as gamification (e.g., rewards), the concept of Self Determination Theory (SDT), and Uses and Gratifications Theory (U&GT). As Scheibe et al. (2016, p. 9) explain "[j]ust as the rise of online databases and digital libraries sparked off a generation of research in online searching, so too social media should stimulate a new wave of research and theories focusing on other types of information behavior such as asking, answering and information integration." Now, a new wave of ICTs sparked off, namely ATTs, which leads to a similar phenomenon. This research object has huge potential from the information science perspective, as the component information and users' interaction with it is a main aspect of ATTs. To investigate this and the second axis of the conceptual triad, (Figure 1.1) this thesis adapted several information-related concepts, especially from a broadly defined information behavior concept. Overall, the following concepts and aspects form the framework of this thesis to outline the responsibility of information science. This framework offers a holistic view on the users of activity tracking technologies. The components that are shaping the IB framework in this thesis are:

- Information Literacy,
- ISE Model,
- Privacy-Related Behavior,
- Uses & Gratifications Theory,
- Self-Determination Theory,
- Gamification

Interestingly, the information use and, thus, the IB is further shaped through information literacy. According to Association of College & Research Libraries (1989, §1-3), "Information literacy is a survival skill in the Information Age." The Association of College & Research Libraries (1989, §17-19) explains, that "to be an information literate, a person must be able to recognize when information is needed and have the ability to locate, evaluate and use effectively the needed information" no matter "whether the information they select comes from a computer, a book, a government agency, a film, or any number of other possible resources"(Association of College & Research Libraries, 1989, §2-3). The produced manifold information is accessible anywhere and anytime. When transferring this concept to the activity tracking technology domain, one would rather speak of health information literacy. The information offered by those ATTs (heart rate, blood sugar) is assigned to health and fitness-related specific topics and requires specific knowledge. Both, recognizing that there exists a health and fitness-related information need and the usage and assessment of that information, can be assigned to the concept of Health Information Behavior. Eriksson-Backa, Ek, Niemelä, and Huotari (2012, p. 84) state that "[a] related concept that describes health-related information behaviour, including needs, seeking and use of information related to health or medicine is health information literacy [...]." According to the Medical Library Association (2005, p. 1), Health Information Literacy (HIL) enables to "recognize a health information need; identify likely information sources and use them to retrieve relevant information; assess the quality of the information and its applicability to a specific situation; and analyze, understand, and use the information to make good health decisions."

The conceptual triad by Shin et al. (2019) offers vast potential to stress out that user interactions and the information provided by the WATs need to be investigated more intensively in the future while also concentrating on Information Literacy (IL) and IB. Ilhan et al. (2020, p. 2) emphazise that "[t]he crux of these challenges is the complex interplay among the self-tracking technologies, the information generated by them, and the people who use them."

Within the information science discipline not only the data-centric investigations are crucial, but the axis illustrating the association between "People (Users) and Technology" is pivotal. The second axis plays an essential role in information science as the discipline also deals with the evaluation of ISs. According to Schumann and Stock (2016, p. 2), "[c]omplex information services satisfy complex human information needs." Therefore, Schumann and Stock (2016) developed the Information Service Evaluation (ISE) model to investigate complex information services by merging different theoretical frameworks such as Technology Acceptance Model (TAM), Technology Acceptance Model 2 (TAM2), and Unified Theory of Acceptance and Use of Technology (UTAUT). They argue that all those dimensions (the perceived information service quality (D1), the information user (D2), and the information acceptance (D3)) are crucial to investigate if the investigated information service is satisfying the needs of a user. The acceptance and use of information services depend also on IL, which means the more users know their information need and know how to use the information, the more they adapt and use information services (Shin et al., 2019). Therefore, it is not only important to consider different levels of information literate users, but also to consider different knowledge levels of users regarding an information service (Schumann & Stock, 2016).

Finally, according to Shin et al. (2019), the aspect of privacy, especially from an information science perspective is less investigated. Fietkiewicz and Henkel (2018, p. 442) also stress out that "more extensive user-oriented research going beyond users' privacy preferences would give scholars and practitioners more relevant insights." Givens (2015) explains that, we, as information professionals, need to educate people regarding information privacy. She said "[p]art of our duty as information professionals is to educate others about information privacy"(Givens, 2015, p. 10). Therefore, privacy literacy can also be assigned to the concept of IB. Givens (2015) explains that evaluating online information requires to be aware of the risks. "If an individual does not understand the risks he or she takes when searching, accessing websites, and providing information online, that person cannot accurately evaluate the value of the information" (Givens, 2015, p. 54).

This general overview aimed to emphasize the role and responsibility of information science research regarding ATTs. Health Information Behavior (HIB) is not much longer characterized through only seeking or searching for information online. Already F. Zimmer et al. (2018) showed that to understand a user's IB a wide-ranging concept is needed. With this in mind this thesis examines the emerging technologies from a holistic view and thoroughly reveals different aspects. The following section will provide a thematic overview shaped by the three parts of this thesis. The thematic overview of each part (Part 1-3) will lead to the three Research Question (RQ) of this thesis.

1.1 Part 1: Self-Quantified Information Behavior

Lupton (2016, p. 2) describes self-tracking as an activity that is "directed at regularly monitoring and recording, and often measuring, elements of an individual's behavior or bodily functions." Self-tracking can be enabled through ATTs. Those ATTs are mainly worn on the wrist and measure different health and fitness-metrics such as steps, heart rate, sleep quality and duration, distance, burned calories and much more depending on the device itself.

Researchers such as Li, Dey, and Forlizzi (2010) and Epstein, Ping, Fogarty, and Munson (2015) tried to conceptualize why people are using Personal Informatics Systems (PISs) to self-quantify their behavior and to what extent those PISs can support users. The main characteristics of PISs are that they "inform people about themselves" (Li et al., 2010, p. 557). They also point out that for meeting those users needs (to self-quantify their behavior), the PISs "need to be effective and simple to use" (Li et al., 2010, p. 557). Interestingly, Jarrahi, Gafinowitz, and Shin (2018, p. 444) explain, "over time, information from the Fitbit device became less meaningful or less relevant for many participants, as its representations became routine and lacked sufficient novelty to maintain their interest." This is similar to the insight given by Gouveia, Karapanos, and Hassenzahl (2015, p. 9) "that users come to disengage with the tracker as they become more likely to meet their daily walking goals." Current investigations according to the systematic literature review by Shin et al. (2019, p. 6) show that 78 articles are assigned to the theme acceptance, adoption, and abandonment. Shin et al. (2019) stress that acceptance and adoption are addressed adequately. However, their introduced investigations show that the studies provide small samples (between 8-100 participants). Further, those studies are not concentrating on cultural differences or similarities. In Germany, some public health insurance companies such as AOK Nordost are offering a grant to buy a wearable or a fitness tracker. Others, such as AOK Plus are offering points for a user's account within the bonus program if one buys wearable. Other public health insurance such as the Techniker Krankenkasse (TK) offer their own mobile application where collected steps could be transferred in points to receive gifts or to pay out dividends. Users in the USA can also share their data with health insurance. **Chapter 2** of this thesis ties on those insights and focuses empirically on the perceived service quality and acceptance of wearable activity tracking users in Germany and the USA. To the best of our knowledge, the investigation was the first one in (2017-2018) that focused on the cultural aspect (here, users from Germany and the USA). Overall, the article questioned 674 participants through an online survey distributed from March 25, 2017, to June 08, 2017. The insights of Chapter 2 contribute in several ways to previous studies. First of all, it supports understanding of the extent to which the information offered by the wearables impacts users' behavioral change. Second, it offers insights to what extent users would like to share their data (information behavior) with health insurance companies and doctors. For example, in Germany, health insurance companies are also trying to motivate users to be physically active. In the United States, the health care system differs from the German one. Here the publication offers first insights if there might be differences regarding the willingness to share data. As current studies rather tried to generally cover the users' motivation (explorative), also shown by Shin et al. (2019) and the impact of those trackers on their behavior, this study draws on a theoretical ISE model.

In comparison to Chapter 2, **Chapter 3** will provide insights into the information behavior and the concept of information literacy while concentrating on Fitbit users. While users have different reasons why they are using ATTs (see for example Feng & Agosto, 2017, 2019; Rooksby, Rost, Morrison, & Chalmers, 2014) it is barely investigated if users are assessing those information, reflecting on those information and adapting their behavior based on different levels of information. McKinney, Cox, and Sbaffi (2019) investigated users of activity tracking technologies from an information literacy perspective. According to the findings from a study by McKinney et al. (2019, p. 11), "tracking is used in different ways by different groups, but in all contexts, it is an information intense activity based on gathering, interpreting and managing data mediated by various devices and apps." Considering activities such as gathering, interpreting and managing and in the end effective use of those information, people need to develop information literacy as "the effective and safe use of tracking" depends on it (McKinney et al., 2019, p. 2). But is this an assumption that must be met by every user? Participants' views, provided by Rooksby et al. (2014), foreshadow that the documentation style is also somehow perceived as endorsement/confirmation that the user is physically active. According to Rooksby et al. (2014, p. 1168), "documentary tracking was not usually a long-term endeavor. Little tracking was being done for the sake of building up a stock of data about life." Furthermore, the usage duration can influence how the information is being assessed and used. Epstein, Kang, Pina, Fogarty, and Munson (2016, p. 838) explain that "[a] person who has tracked consistently is more likely to understand their daily and weekly habits, and may therefore prefer seeing longer-term representations of their data." Users information behavior regarding activity tracking technologies opens up a new and valuable research gap for information science researchers. Critical questions arise such as which information are needed and why? Rooksby et al. (2014) explained, some users might be interested in statistics and therefore welcome aggregated data by wearables and the diagrams they offer. But some people do not want to be overloaded with statistics at all. Further challenges are mentioned by Fritz, Huang, Murphy, and Zimmermann (2014). They summarized that the numerical information, one main characteristic of WATs, motivates users. The risks that arise with the numerical feedback or numerical information is the understandability of those numbers. Fritz et al. (2014) explained that users are following goals such as reaching high numbers, but "[t]his appeared to be the case regardless of whether the numbers were concretely understandable" (Fritz et al., 2014, p. 492).

Yet, only the studies by Feng, Li, and Agosto (2017) and Feng and Agosto (2019) thoroughly investigated how the users manage their personal health information collected by those wearables. Further, as previous investigations revealed, the reasons why users are using those wearables and continued use differ. Some users have a specific goal in mind, others are curious about the technology, and others want to identify patterns to improve their behavior. Therefore, Chapter 3 will focuse on the usage of different types of information provided by an ATT, in this case, one of the most popular ATTs - Fitbit. In this investigation, there are different types of offered information included to better understand the use of that information depending on the information needs. This investigation gives insights into what kind of information needs the users have and what kind of information type meet the users' needs. Here the investigation focused on three different types of information, namely raw data (the actual number of steps, heart rate, sleep duration), aggregated data (e.g., diagrams, richer data visualization), and explanations (e.g., heart rate zone and sleep stages' characteristic explanations). The concept of HIL supports understanding users' health information behavior and the extent to which those skills such as analyzing, reflecting on, and assessing data are needed. Participants in this study subjectively evaluate if they can use those information, perceive them as understandable and can reflect on explanations provided by Fitbit. For this investigation an online survey was distributed and answered by 631 Fitbit users.

Information can help not only to gain knowledge but to learn for a lifetime. Some ATTs are equipped with gamification elements to motivate a user to be physically more active and to engage with the application or wearable. According to Zichermann and Cunningham (2011, p. xiv) gamification is "[t]he process of game-thinking and game mechanism to engage users and solve problems" and according to Deterding, Dixon, Khaled, and Nacke (2011, p. 10), one of the common definitions is, "'Gamification' is the use of game design elements in non-game contexts." There also exists another definition, as gamification also depends on the context where it is used or rather applied. According to Huotari and Hamari (2012, p. 19), it is a "process of enhancing a service with affordances for gameful experiences in order to support user's overall value creation." A study by Nelson, Verhagen, and Noordzij (2016, p. 369) showed that "gamification and readability seemed to be the strongest empowerment determinants." **Chapter 4** is a theoretical investigation using content analysis to understand the gamification elements' potential to support learning towards changing health behavior. Goal setting is one of those gamification elements. Gouveia et al. (2015) explained that goal setting is a common behavior change technique. They describe it as one of "the most popular, theoretically informed and empirically grounded approach to instill behavior change" (Gouveia et al., 2015,

p. 2). Fritz et al. (2014) explain "[i]ronically devices that initially helped foster engagement in fitness sometimes became too naive to support increasingly sophisticated fitness priorities" (Fritz et al., 2014, p. 492). It could also happen that the goals are changing over time or that one's own goal is not matching with the system's goal (Gulotta, Forlizzi, Yang, & Newman, 2016). Epstein et al. (2016, p. 830) stress out that "designers must consider not only what information they present to a tracker, but also design how they frame that information." For example, authors showed that users who used the Fitbit longer are much more motivated to see on how many days they were physically active instead of users who only use it in short-term. Further, Gulotta et al. (2016, p. 286) explain "a number of challenges remain that limit the usefulness of these systems. People frequently stop using [personal informatics] PI systems without having achieved their goals; those who do reach their goals may lack motivation to continue using the system to maintain their progress or to refine their goals over time." Gouveia et al. (2015) explained that the implementation of textual feedback needs to consider that textual feedback should be novel. If the text messages are familiar to users, the engagement with an application is not increasing (Gouveia et al., 2015).

ATTs are to a different extent equipped with gamification elements such as leaderboard, levels, feedback, progress bars, challenges and much more. These gamification elements can award users for being physically active and reaching a goal. Motivational affordance enables users to pursue goals, system-defined or self-defined goals, toward reaching a healthier behavior. Especially the later one can be crucial for integrating gamification elements, such as progress bars and goal-setting possibilities. The complex construct of motivation SDT raises the question of which elements might be useful for which motivational source and how is the information needed to be designed? As one of ATT's main components is the offered information, insights into how gamification and the complexity of information play a role together are valuable, especially from the perspective of an information professional. Therefore, Chapter 4 will provide insights into how to implement and develop useful and individual information considering the concept of gamification. Overall this chapter investigated ten mobile corresponding applications of WATs and compared the integrated gamification mechanics to identify to what extent users engagement to reach a long-term healthier behavior change can be potentially accomplished.

Based on the theoretical overview (see Chapter 1.1) the presented Chapters 2, 3, and 4 will offer the possibility to gain insights into the self-quantified information behavior of ATTs users and answer the following RQ:

RQ1: To what extent do the ATTs enable effective self-quantification behavior from an information science perspective?

With those investigations it becomes clear that a new era for information science research has emerged. Even though many studies are investigating activity tracking technologies, only a few studies related to users' sharing behavior within social media and fitness and health-related content. Since activity tracking technologies are already equipped with sensors and gamification elements to support users, why are those users joining those groups? Regarding today's omnipresent availability of information this a more important point to better understand users information behavior, especially having the broad definition and the model of (Scheibe et al., 2016; F. Zimmer et al., 2018) in mind.

1.2 Part 2: Information Behavior within Health and Fitness-Related Facebook Groups

Facebook has many fitness and health-related Facebook groups. There is a private group called *Fitbit Charge 2 Group* with about 9,000 members, or *Fitbit UK*, also a private group, with more about 6,500 members. Regarding the HIB of wearable activity tracking users, why did they join fitness and health-related Facebook groups? Do they have an information-related need or would like to disseminate their self-quantified data?

As new ICTs emerge, information science research keeps investigating the information behavior in a broader sense (Scheibe et al., 2016). Apart from the WATs that are providing information users' behavior takes place online. From an information science perspective the investigation of IB within social media platforms increases. The U&GT enables to receive answers to questions such as *why* are users using specific media, and to what extent do those media meet their needs. Krcmar (2017) explains the difference between gratifications sought and obtained. According to Krcmar (2017, p. 2), "gratifications sought are those that we bring to a media use situation," such as passing the time, learning something, or socializing. On the contrary, gratifications obtained "are those that result from a media use situation." According to Palmgreen, Wenner, and Rayburn (1980), gratifications sought are not necessarily also obtained when deciding to use a medium. According to F. Zimmer et al. (2018), U&GT is part of the broader concept of IB. Gratifications sought can be understood as "needs" (Krcmar, 2017). F. Zimmer et al. (2018, p. 435) explain the different gratifications: "*information* means the motive of finding knowledge, *person identity* is related to our motive to define our motive to define our identity; *entertainment* comprises escaping from problems, relaxing, filling time, or sexual arousal; *social interaction* is the motive to interact with other people." Apart from understanding why users are using those health and fitness-related groups, the need (motivation) within the IB concept by F. Zimmer et al. (2018) is crucial.

The long and short-term use of WATs can be influenced by human motivation as well as the reason to join those introduced groups. According to Ryan and Deci (2000, p. 69), "[m]otivation concerns energy, direction, persistence and equifinality – all aspects of activation and intention" and more important "[m]otivation produces" (Ryan & Deci, 2000, p. 69). Further, according to Ryan and Deci (2000, p. 54), "to be motivated means to be moved to do something." Here, there is the talk of SDT. According to Ryan and Deci (2000, p. 69), SDT enables "to identify several distinct types of motivation, each of which has specifiable consequences for learning, performance, personal experience, and well- being." They are dividing SDT into intrinsic and extrinsic motivation and are also introducing the reason not to do something (ammotivation) (see Deci & Ryan, 1985; Ryan & Deci, 2000). People who are intrinsically motivated "experience interest and enjoyment, they feel competent and self-determining, they perceive the locus of causality for their behavior to be internal, and in some instances they experience flow" (Deci & Ryan, 1985, p. 34).

Apart from intrinsic motivation Deci and Ryan (1985) also talk about extrinsic motivation. Primarily, the distinction to what extent the behavior is extrinsically motivated is differently self-determined. Extrinsically characterized behaviors, where the motivation is based on one's values and desires, is more self-determined than those where people perceived pressure (Deci & Ryan, 1985). Overall there are four subtypes of extrinsic motivation (external regulation, introjected regulation, integrated regulation and identified regulation) (Ryan & Deci, 2000). Even though the concept of motivation is finely divided into intrinsic and different manifestations of extrinsic motivation, this does not necessarily mean that someone can only be intrinsically or extrinsically motivated. For example, a study by Schaffarczyk and Ilhan (2019) showed that users of ATTs were both intrinsically and extrinsically motivated. Attig, Karp, and Franke (2019) investigated usage motivation of ATTs users as well from a perspective of SDT and also reported that some of the participants were extrinsically as well as intrinsically motivated. They also implicate that "[u]sage motivations were related to tracker usage intensity. The more self-determined and autonomous the motivation is perceived, the higher the current and estimated future tracking intensity is" (Attig et al., 2019, p. 7).

With emerging ICTs, where social media shapes our everyday life, and dissemination and consumption of information are omnipresent, this thesis focused on fitness and health-related Facebook groups. **Chapter 5** aims to better understand ATT users' motivation and need to join those groups, and if there is a connection between the use of the ATT and the reason to join those Facebook groups. Hereby, the investigation identified different gratifications by applying U&GT and investigated if the reason to join those groups was caused by extrinsic or intrinsic motivation according to SDT. For example, are users joining those groups because they enjoy the community feeling (intrinsic motivation), or did they join because they were forced to do it (extrinsic motivation)? It comes as no surprise that those Facebook groups are accepted if one looks at how many of those groups exist and how many members joined them. According to Krcmar (2017, p. 1), "uses and gratifications research focuses on media use, asking what motivates various kinds of media use" and supports "understanding why we choose the media we do and how we use it." From the U&GT perspective, these investigations offer insights into the need to join those groups' and groups' potential. Questions such as to what extent users seek information within those groups or if they would like to be entertained arise. But not only the sought gratifications are investigated, but the thesis will also answer if those groups are offering information and the possibility to be entertained (gratifications obtained).

Chapter 5 enables an insight into 20 activity tracker and fitness-related Facebook groups. Overall 445 ATTs users participated via an online survey from January 2019 until February 2019. As this chapter did not investigate gender or generation determined differences the following **Chapter 6** will offer insights into these aspects. There are only few investigations that concentrate on the U&GT approach to understand if men and women behave differently.

Questions that arise: Do men and women joint to the same extent those groups based on the information need they recognized? Can gender and generation-determined differences be identified? For example, do men and women, or the younger and the elder generation, differentiate regarding the desire to share information about oneself (posting reached goals)? Based on the broader sense of IB, the concept also includes the production of information and not the only use. Chapter 6 based on Chapter's 5 survey results narrowed the sample to Fitbit Facebook groups to enable an homogeneous base. Therefore, 268 participants from 445 where investigated with focus set on gender and generation- determined differences.

Those two investigations (Chapter 5 and Chapter 6) will enable a thorough insight to what extent users seek information within those groups and apart from this gratification if there are other reasons (need to socialize, to be entertained or self-realize themselves) as well. Chapter 6 will also provide insights if those sought and obtained gratifications and motivational reasons differ between genders and generations. These two investigations will answer the overall RQ:

RQ2: Which gratifications and other motivational sources lead ATTs users to join health and fitness-related Facebook groups and to what extent do users' characteristics influence information behavior?

Especially with having social media in mind and the sharing of information and health and fitness-related information leads to the third part of this thesis. Since the collected health and fitness-related information discloses information about users' physical and health behavior, to what extent are users concerned about misuse or hacking of that information? The next part (Part 3) will concentrate on privacy-related behaviors regarding fitness and health-related information.

1.3 Part 3: Self-Quantified Privacy-Related Behavior and Concerns

According to Wolford (2020), there is a difference between protection and privacy. "Data protection means keeping data safe from unauthorized access. Data privacy means empowering your users to make their own decision about who can process their data and for what purpose." This raises critical questions. Do users of ATTs have privacy concerns but are still using the technology? The omnipresent digitalization and the self-quantification with those ATTs leaves manifold data collected 24/7 about users in digital clouds. This fact makes it interesting for hackers to try to get access to those data. Headings such as "Under Armous says 150 million MyFitnessPal accounts compromised in data breach"[1] hit the headlines in 2018. According to Leonhardt (2019), the UnderArmour (MyFitnessPal) data breach hack is one of the top 10 big data breaches with 143.6 million records hacked. In 2018, this was not the only

[1] https://www.theverge.com/2018/3/29/17177848/under-armour-myfitnesspal-data-breach-150-million-accounts-security

headline regarding health and fitness applications covered in news. For example, The New York Times published the headline "How Strava's Heat Map Uncovers Military Bases."[2] But again: Why are users using those wearables then? Based on those observations that today's society is continuing to use ATTs and other ICTs as well while disclosing information about oneself - this could be explained by the privacy paradox. Several investigations regarding the disclosure of information explain that users, even if they have privacy-related concerns, still adapt and use those technologies. Apart from the privacy paradox phenomenon, there is also the talk of privacy calculus. For example, Cox et al. (2017, p. 194) revealed that "[m]any were aware of data privacy issues, but some felt since the tools were free, the use of their data was a fair exchange." Even though M. Zimmer, Kumar, Vitak, Liao, and Kritikos (2020, p. 1031) did not describe it as the Privacy Calculus, stating that "[o]verall, the perceived benefits of using fitness trackers greatly outweigh drawbacks among our participants" indicates the phenomenon of Privacy Calculus. Barnes (2006) also emphazises "[m]any people may not be aware of the fact that their privacy has already been jeopardized and they are not taking step to protect their personal information from being used by others." Therefore, it seems that users' information disclosure and privacy-related information behavior is describable as not in line with users' concerns. The thesis calls to action: What is the responsibility of information professionals? Where do we face challenges? Do we need to support users in raising awareness about the risks of information disclosure, and developing a sustainable privacy-related information behavior (e.g., managing privacy-related settings, caring about collected data)?

The following chapters 7, 8, and 9 will offer insights into the topic of privacy concerns and privacy-related information behavior. To guarantee safe and fair use of those devices and protect users' privacy, research, and politics and legislation endeavors from advancing data privacy and security and offering a sustainable data privacy environment. Since May 2018, General Data Protection Regulation (GDPR) tries to provide better privacy regulation within European Union. Those top-down rudiments try to handle in everyone's interest. They aim to enable the safe use of those ATT and provide a sustainable privacy environment. How do users perceive that legislation? Those top-down decisions and implementation influence the trust in companies and government. Questions that arise from an information science perspective: Do those top-down decisions also influence the information disclosure behavior of ATTs users? Are users taking less or more responsibility regarding the protection of their online information?

Therefore, **Chapter 7** will offer insights regarding users attitude towards GDPR's effectiveness. This could have an influence on how people share and use wearable activity tracking technologies. This chapter offers insights to what extent participants from Europe believe in GDPR's effectivity and are aware of it. Conducting an online survey, the article represents overall 167 answers from the EU (mainly including participants from Germany, U.K., Poland, and Austria).

Independent from the legislative level (top-down approach), ATTs are collecting and storing data in digital clouds 24/7. Health and fitness-related data can burden parties, especially with

[2] https://www.nytimes.com/video/world/middleeast/100000005705502/big-data-big-problems-how-stravas-heat-map-uncovers-military-bases.html

having in mind that unauthorized users can have access to it or that those data could be shared with doctors and health insurance. What kind of information are they collecting and storing? Starting from data, you need to share during registration (such as email address, credit card information (if required), birth date, name), and data that is collected while using the WATs. Some are permanently tracked, such as steps or heart rate. Other data pieces, such as Global Positioning System (GPS) can be activated whenever needed, for example, during the use of an application (e.g., Strava). **Chapter 8** provides insights into an empirical study concentrating on 590 participants whereas 330 are current users, 253 non-users and 53 former users from the EU and the USA. Thereby the focus lies on the perceived sensitivity of different data pieces and concerns regarding privacy and security risks. While the thesis mainly focuses on the currents users' investigation, former users and non-users enable a holistic insight into whether privacy concerns might be an indicator to stop using those ATT at all or even not to start to use them.

But not only the legislative level is crucial. Users themselves play a crucial active role and are responsible for privacy-related behavior, primarily concentrating on managing the collected information. Especially questions referring to data privacy, such as, are users able to make decisions (e.g., adaption of privacy settings), refer to privacy literacy. Privacy literacy "focus on the understanding of the responsibilities and risks associated with sharing information online [...] [and] aligns more closely with critical thinking" (Wissinger, 2017, p. 380). A look into the Fitbit application showed that the privacy policies refer to the website of Fitbit. Fitbit explains that users "will learn about the data [they] collect, how [they] use it, the controls [they] give you over your information, and the measures [they] take to keep it safe." In this statement, Fitbit is including both data security (keeping information safe) and data privacy (control over your information). But how many users are reading those privacy policies?

M. Zimmer et al. (2020, p. 1031) concluded that "user may adopt these technologies without deeply engaging in data sharing practices or privacy policies of the companies collecting their data." Even though Obar and Oeldorf-Hirsch (2020) investigated the privacy-related information behavior regarding social networking services, privacy policy, and terms of service (TOS) are similarly modeled. Obar and Oeldorf-Hirsch (2020, p. 140) explained that the participants "often ignore privacy and TOS policies for social networking services. [...] When people do read policies, they often remain on the relevant pages just long enough to scroll to the 'accept' button [...]."

According to Culver and Grizzle (2017, p. 14), "Media and information literate individuals are more empowered to make informed decisions about their privacy online and offline, among other things." They mentioned as well that "[i]ndividuals often agree to these usage rules [terms and conditions] without comprehending the details of how their data will be used, copied, shared or altered" (Culver & Grizzle, 2017, p. 23).

Further, McKinney et al. (2019) explained to what extent privacy aspects are connected with IL. "The extent to which people are aware of issues to do with the privacy of their personal data held in mobile apps or shared online" and "[u]nderstanding potential issues around privacy and security of data" is characterized as part of IL (McKinney et al., 2019, p. 3).

Chapter 9 will offer cultural insights into the privacy-related behavior of ATT users. This chapter will answer questions such as to what extent participants of ATTs and applications will differ or have similarities regarding their privacy-related information behavior. To what extent are those users taking responsibility and would they request the deletion of the data if they stoped using the ATT? More important, do those users know that they can request the deletion of data? Answering those question is crucial within the information science field where information professionals can support users and raise further awareness. To what extent are bottom-up approaches, such as the self-management of privacy-related settings and information advisable?

These three chapters (Chapter 7-9) will answer the overall research questions (RQ):

RQ3a: What are the privacy concerns regarding ATTs?

RQ3b: What is the privacy information behavior of ATTs users?

Most of the chapters are exploratory studies aiming to provide empirical findings. Therefore, the methodical approach, here survey, is one of the core approaches to answering the overall research questions except for Chapter 4. The next subchapter will provide insights into the benefits of these two methods and introduce their main characteristics.

1.4 Methods

1.4.1 Survey

According to Connaway and Radford (2017, p. 97), "[t]o survey means to look at or to see over or beyond or, in other words, to observe." There are different types of surveys, such as the exploratory survey or analytical and descriptive survey (Connaway & Radford, 2017).

The most applied type of survey in the thesis is descriptive surveys, as the "purposes of descriptive surveys are to describe characteristics of the population of interest, estimate proportions in the population, make specific predictions, and test associational relationships" (Connaway & Radford, 2017, p. 101). ATTs are rarely investigated from an information science perspective, therefore, the surveys conducted for this thesis could also be characterized as "insight-stimulating" surveys (Connaway & Radford, 2017, p. 99) as a special kind of exploratory survey. Connaway and Radford (2017, p. 99) explain, "[w]here there is little experience to serve as a guide, researchers have found the intensive study of selected examples to be a useful method of stimulating insights and suggestions hypotheses for future research." For example, the approach of Chapter 3 is characterizable as an insight-stimulating explorative study. The study is based on two examples of Fitbit (heart rate zones and sleep stage characteristics explanations) and tries to better understand ATT users' HIB. A survey consists of different steps which will be explained in the following subsections.

Sampling and Collection

There are different approaches, such as the probability sample, simple random sample and the nonprobability sample. The surveys in this thesis are all assigned to the nonprobability sample. It is a challenge to reach out to all users of WATs all over the world. Therefore, subtypes of nonprobability samples, such as the purposive sample and self-selected sample, are used. Indeed, the nonprobability sample has weaknesses, and therefore, the results derived from those investigations are difficult to generalize (Connaway & Radford, 2017). But, as those studies offer first insights, the results overall offer implications on how users might be using the provided information and what aspects could influence the self-quantified behavior.

Design and Pretest

The surveys developed and analyzed within this thesis consists of different types of questions. Examples of fixed-response or structured questions are yes and no questions and an evaluation scale (the so-called Likert scale). One advantage of those fixed-response questions is that they "more easily accommodate precoding, in that the possible responses are generally known and stated" (Connaway & Radford, 2017, p. 111). Apart from advantages, there also disadvantages such as that "a limited set of possible replies can force respondents to select inaccurate answers" (Connaway & Radford, 2017, p. 112). All the surveys used in this dissertation underwent a pretest. Connaway and Radford (2017, p. 123) explain the advantages of pretests: "A pretest gives the researchers an opportunity to identify questionnaire items that tend to be misunderstood by the participants or do not obtain the information that is needed."

Analyzing and Interpreting

The applied statistical analyses in the investigation are based on the nature of the collected data. "[T]he nature of the data to a large extent determines the statistical techniques that can be used legitimately" (Connaway & Radford, 2017, p. 177). Before analyzing the quantitative data with the statistical software the coding of data is required. As Connaway and Radford (2017, p. 179) explained "[o]nce the categories have been established and data 'assigned' to them, it is necessary to convert the new data or responses to numerical codes, so that they can be tabulated or tallied." Overall in the chapters (2-4 and 6-9) both descriptive as well as inferential statistics were applied. While descriptive statistics (e.g., absolute, median, interquartile range) describe the distribution of answers within the given sample, inferential statistics offer the possibility "to test hypotheses using tests of statistical significance to determine if observed differences between groups or variables are 'real' or merely due to chance" (Connaway & Radford, 2017, p. 188). Depending on the scale of the variables, different parametric and non-parametric statistics can be used. According to Connaway and Radford (2017), as nonparametric statistics (e.g., Mann-Whitey U-test, Spearman Rank-Order Correlation) are considered to be distribution-free, they are mostly used for the analysis within this thesis (Connaway & Radford, 2017). For the statistical analysis of the data, different versions of the statistical software SPSS were used. This software is developed and offered by IBM and is common within the Social Sciences (Connaway & Radford, 2017).

1.4.2 Content Analysis

Apart from conducting surveys, content analysis (Krippendorff, 2004) was applied. Julien (2008, p. 120) explained, "[w]here quantitative content analysis is helpful in answering 'what' questions, qualitative content analysis can be helpful in answering 'why' questions and analyzing perceptions." To offer insights into the probable effects of gamification elements implemented within ATTs, content analysis enabled not only to show if those gamification elements are implemented or not but also to investigate their association to different theories and to what extent they could influence or rather motivate users. Julien (2008, p. 120) explain that content analysis offers the possibility not only to receive derived items, but "reveal recurrent instances of 'items' or themes, or they may reveal broader discourses." Julien (2008, p. 120) explain also that "[c]ontent analysis is the intellectual process of categorizing qualitative textual data into clusters of similar entities, or conceptual categories, to identify consistent patterns and relationships between variables or themes."

As gamification elements itself within the realm of ATT were barely investigated regarding their existence and how they are correlated to motivation sources and goal-oriented factors, Given (2008) explain that "qualitative methods are best for addressing many of the *why* questions that researchers have in mind when they develop their projects." Applying content analysis (four-eyes principal) aimed to create a theoretical foundation for future empirically based studies.

These two presented methods represent viable approaches within the information science to conduct user-centered studies and in-depth theoretical examinations. The applied methods are used in the following investigations to answer the three main research questions in the next sections.

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Part I

Self-Quantified Information Behavior

2 10,000 Steps a Day for Health? User-based Evaluation of Wearable Activity Trackers

Ilhan, A., & Henkel, M. (2018). 10, 000 Steps a Day for Health? User-based Evaluation of Wearable Activity Trackers. In *Proceedings of the 51st Hawaii International Conference on System Sciences* (pp. 3376-3385). ScholarSpace.
Available: http://hdl.handle.net/10125/50316

Abstract *We present the results of a survey on perceived service quality and service acceptance of activity trackers with a focus on country-based differences (US and Germany). The mutual influence of perceived service quality and service acceptance is being investigated. A new research focus based on activity trackers is the topic of medical health funds. Are users ready to share activity data with health insurance and expecting rewards in return? This study (N=803) supplements previous research which is mainly based on small sample sizes or qualitative results. Our research model is based on the Information Service Evaluation (ISE) model which includes common models such as TAM and UTAUT. Results show that aspects such as Fun, Gamification, Impact and Usefulness are very important regarding activity tracker use. Furthermore, user's opinion on the support of medical healthcare funds and reducing medical fees is rather positive and significantly differentiates between US and German participants.*

2.1 Introduction

2,000 steps yesterday, 4,000 steps today and maybe 8,000 steps tomorrow. How many steps did you do today? Nowadays, activity tracking, e.g., the counting of steps, is nothing unusual anymore. The demand for smart wearable products in the health care domain such as activity trackers, also known as actigraphs, is growing rapidly. About 80% market share is defined by basic wearables (e.g., Fitbit, Xiaomi, Garmin) and 20% by smart watches (e.g., Apple Watch, Samsung, Gear, BBK) IDC (n.d.).

In today's age, the collection of individualized data through wearable sensors or other means of Information and Communication Technology (ICT) has potential for monitoring and improving citizen's health welfare: "Emerging persuasive technology and ubiquitous wearable sensors offer much promise for improving health and fitness practices" (Fritz, Huang, Murphy, & Zimmermann, 2014, p. 487). An activity tracker can have different functions, such as counting steps, active minutes, calories burned, distance covered or providing sleep analysis as well as measuring and documenting the heart rate, food intake and much more (Figure 2.1).

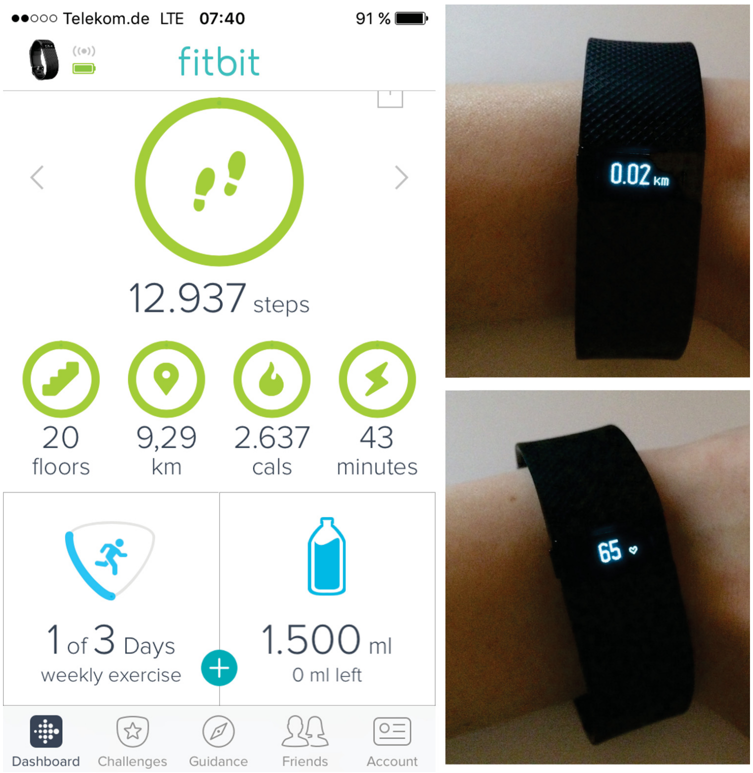

Figure 2.1: Fitbit app (left); Distance and heart rate shown on the tracker (right)

The possibility to be one's own administrator and account for one's own self-improvement through the functions of activity trackers (data collection or activity mining), is defined as self-quantification (Day, 2016; Li, Dey, & Forlizzi, 2010). Self-quantification is possible through a "system that helps people collect personally relevant information for the purpose of self-reflection and gaining self-knowledge" (Day, 2016, p. 2; Li et al., 2010).
Indeed, users might want to observe and document their own fitness activity and health information (Schaefer, Ching, Breen, & German, 2016), for self-reflection or self-improvement, but there might be other reasons as well. We would like to learn more about the "typical" activity tracker user and how people feel motivated to take care of their own health and fitness activity by using activity trackers. Beyond the fact that people could manage their own health and fitness level by wearing activity trackers, what about health insurance funds? Should they reward customers for documented activity and should health insurance funds even have access to collected fitness and health data to begin with? The purpose of this empirical study is to find out more about the user experience by using information systems, here activity trackers, and the actual influence on their behavior. But how does the purpose of this study connect to similar research?

In a study by Fritz et al. (2014), the results show that consumers of fitness tracking wearables use the collected data as feedback to change their activity behavior, by taking more steps. Furthermore, their participants confirm that the use of trackers evokes a physical addiction. Related to impact, participants also reported that the real-time awareness supports the improvement of activity. Therefore, real-time awareness might trigger an implicit durable behavior change (Fritz et al., 2014). Giddens, Leidner, and Gonzalez (2017) conducted a study with

53 participants, and found that using an activity tracker has a positive impact on steps taken, which has a positive impact on wellbeing and health. They also found, however, that users reported increased wellbeing regardless of their step count and attributed this to the fact "that the device itself may raise awareness of one's physical activity and the importance of a healthy lifestyle that includes physical movement" (Giddens et al., 2017, p. 3632). Different aspects of fitness and healthcare devices attract attention in the research domain. Some studies focus on the acceptance of healthcare wearable devices and reasons for the adoption of medical and fitness wearable technologies by using models such as UTAUT 2 and PMT for Chinese users (Gao, Li, & Luo, 2015). Some concentrate on the discontinuance of using activity trackers (Clawson, Pater, Miller, Mynatt, & Mamykina, 2015). Shin, Cheon, and Jarrahi (2015, p. 1) call attention to previous studies indicating that "such devices fail to deliver on health benefits in the long term" and that merely collecting data is not the key to success: "[D]ata provided by these technologies are not sufficient to motivate users, and other motivators are needed" (Shin et al., 2015, p. 1). This opinion is shared by Ledger and McCaffrey, too (Ledger & McCaffrey, 2014; Shin et al., 2015). Furthermore, Angulo, Brogan, Martini, Wang, and Clevenger (2016) mentioned that activity trackers are characterized as a facilitator and not primary motivator. Another study concentrating on user motivation conducts interviews with people using fitness tracking systems over a time interval (Day, 2016). But motivation may not be the only factor leading to success, i.e., a change in behavior and eventually the improvement of wellbeing. Other previously analyzed aspects are awareness, goals, and impact of such devices(Fritz et al., 2014). Shih, Han, Poole, Rosson, and Carroll (2015) show in their literature review which challenges and barriers are hidden in aspects of use and adoption of wearable activity trackers. Based on their review, they conducted a study with 26 undergraduate students to analyze the triggering factors. Alturki and Gay (2016) focus on the impact of fitness IT services to analyze the triggering motivation. They point out that most studies concentrate on "feasibility or pilot studies and had small sample sizes" (Alturki & Gay, 2016, p. 203). One topic, which is not solicited as widely in previous research, is the question of linking activity data to health insurance funds. Is it imaginable, that customers agree to health insurance funds having access to their fitness data, enabling discounts on health insurance contributions or rewards, by reaching a certain count of steps?

To gain further insight into these and similar issues, we created an online survey including many aspects that are based on findings of previous researchers. It contributes to previous research in three ways: *First*, we depict results on a big count of participants as most results concentrate on a small sample size up until now. This allows a conclusion based, among others, on the correlation among different aspects, which helps to understand the influence of activity trackers better. Results of this study could be compared to the previous findings. *Secondly*, the survey is built with the aim to enable a country-specific evaluation of data, in this case, between Germany and the United States of America. And *thirdly*, this study enables a contribution to a rather new research angle: health insurance funds. Could they be characterized as a motivator or demotivation related to the use of activity trackers?

2.2 Theoretical Model Framework

We based our questionnaire on the ISE model (Schumann & Stock, 2016). It combines different aspects of traditionally known models, such as the UTAUT (Venkatesh, Morris, Davis, & Davis, 2003), TAM (Davis, 1989), TAM 2 (Venkatesh & Davis, 2000) and MATH (Brown & Venkatesh, 2005) for a holistic evaluation of information systems. In respect to the study's purpose and scope, the perceived service quality and acceptance dimensions of the model are adapted and completed by taking a deeper look at the results and theory of previous research (Figure 2.2). To be more specific, the first dimension (D1) of the model concentrates on the user's perceived service quality of the activity tracker, based on *Ease of Use, Usefulness, Trust, Fun* and *Gamification* (Schumann & Stock, 2016). The factors *Ease of Use* and *Usefulness* are important, as, for example, success and acceptance of a service are, among others, dependent on them (Venkatesh & Davis, 2000). Does the user feel overwhelmed while using a system or is it easy to use with relatively little effort? In this study, *Usefulness* is characterized by the enhancement of fitness awareness and activity. Up until now, we define the following types of the indicator *Usefulness* for the purpose of our study:

- Improvement of fitness level,
- Improvement of health status.

To confirm reliability, Cronbach's alpha (α) was calculated after the end of the survey to "determinate how much the items on a scale are measuring the same underlying dimension" (Laerd Statistics, 2018). The resulting value of .806 is adequate. According to Gefen, Karahanna, and Straub (2003), the factor *Trust* is an essential characteristic related to the quality of a service. Handling of activity data is not limited to counting calories or steps. Analyzing tracked data can result in very personal and sensitive health care information. Kawamoto, Tanaka, and Kuriyama (2014, p. 107) show that with data collected by activity trackers, physical conditions such as "the subjective level of drunkenness, fever, and smoking cessation" can be detected. Therefore, tracked data is a good which should be handled and shared carefully while protecting individual privacy. The *Fun* factor refers to intrinsic motivation – external factors, such as appreciation do not have priority. It actually matters that participants do something just because it "is fun". This factor is a credit to Venkatesh (2000) and is previously defined as perceived enjoyment. One way to further enjoyment of a system's usage is to gamify it. Therefore, the research model (Figure 2.2) includes the factor *Gamification* as it could be characterized as an extrinsic motivation factor. One study shows that 18 participants out of 30 point out "that system goals and rewards influenced on their personal activity and fitness goals" (Fritz et al., 2014, p. 492). This kind of reward is a typical element of gamification. Gamification means "the use of game design elements in non-game contexts" (Deterding, Dixon, Khaled, & Nacke, 2011, p. 10). Gamification in combination with fitness is "one of the most popular utilizations of gamification" (Wylie, 2010, p.1). Not only achievements and awards, but competitions between friends are typical game components that support the own motivation to fulfill individualized health goals (Wylie, 2010). The perceived service quality (D1) of an activity tracker is one aspect for evaluating an information system, its actual acceptance by the user community is another (D3). According to Schumann and Stock (2016), the differentiation between the factors *Adoption* and *Use* is essential. One could use something only a limited time and never again *(Opting-Out)* or one could use something regularly. In our survey, we simplify this issue by asking whether a participant is currently using a tracker or has stopped using it and for what reason. If a service is being used, it could enhance the user during daily tasks, or even have direct influence on their behavior. This is described as *Impact* (Schumann & Stock, 2016). Up until now, we define the following types of *Impact* (α =.785) for the purpose of our study:

- Improvement of wellbeing,
- Addiction,
- Behavioral change.

In many cases activity trackers are seen as tools for raising awareness and for controlling one's own activity level. Reacting to this might result in a change of behavior and eventually in an improvement of wellbeing. A certain dependency or even addiction might not be unrealistic in such a case, as actions can turn into habits and finally compulsion(Turel, Serenko, & Giles, 2011). The last factor is *Diffusion*. Our questionnaire covers different types of *Diffusion* for activity tracker usage and is therefore defined as:

- Dissemination,
- Contagion,
- Group pressure,
- Enforcement.

Users who are satisfied with their activity tracker might recommend or advertise it to their friends and colleagues actively *(Dissemination)* or passively *(Contagion)*: "[A] superior or co-worker suggests that a particular system might be useful, a person may come to believe that it actually is useful, and in turn, form and intention to use it" (Venkatesh & Davis, 2000, p. 189). Does someone only or at least initially use an activity tracker, because everyone in the family or their friends did *(Group Pressure)*? Is it even enforced at work or school, to use an activity tracker *(Enforcement)* as for example at Oral Roberts University in Tulsa, Oklahoma (University Oral Roberts, 2016)? Two research questions (RQ1 and RQ2) are concentrating on these aspects to find out the strengths and weaknesses of trackers (RQ1a) and, by using the ISE model (RQ1b), to analyze the correlation between each item of perceived service quality and service acceptance:

RQ1a: What strengths and weaknesses are recognized by the participants (based on perceived service quality and acceptance) concerning activity trackers?
RQ1b: How do perceived service quality and acceptance of activity trackers influence each other?

At the center of the model, there are the users (D2) with their individual backgrounds. One purpose of the research is the differentiation between Germany and US.

RQ2: Do German participants' opinions differ from US participants', based on the agreement on perceived service quality and acceptance, regarding activity trackers?

Lastly, there is the question of the role of health insurance in the advent of actigraphy. Would a user still use an activity tracker if their insurance was eligible to examine the activity data? Or could it be a motivator to get rewards or discounts for achieving a defined step goal?

RQ3: What are country-specific user opinions and concerns on sharing activity data with health insurance and receiving rewards in return?
Our framework model (Figure 2.2) includes all these mentioned factors and enables the answering of the three research questions.

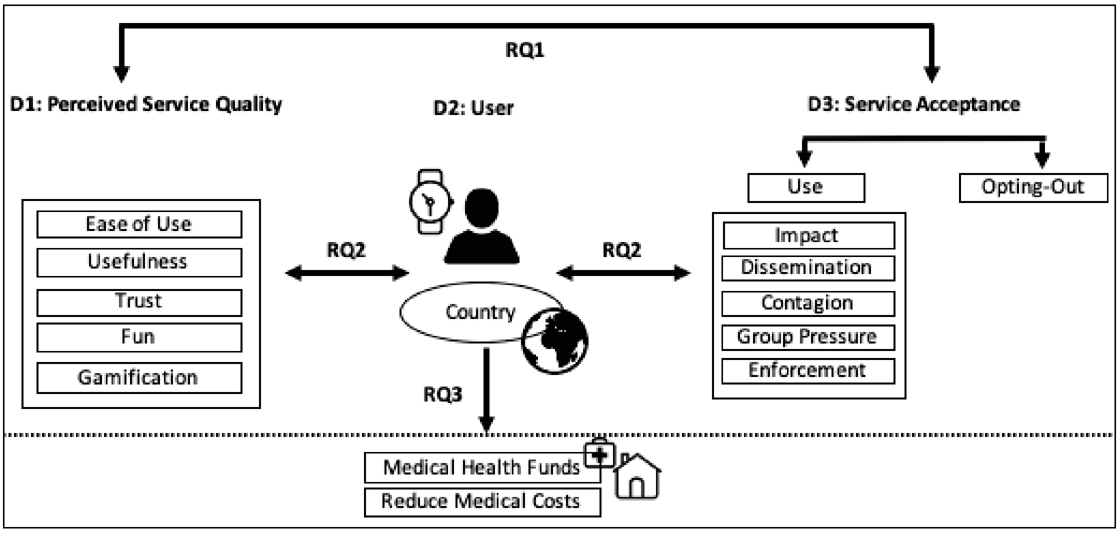

Figure 2.2: Our research model

2.3 Methods

With our three research questions (RQ1-RQ3) in mind, an online survey was developed to generate quantitative data. The German prototype was translated into English to allow a comparison between participants from Germany and participants from the United States. We tried to keep the survey short to lose as little participants as possible, therefore aspects pictured in the research model are each represented via one or two items in the questionnaire. As we merely hope to get an overview at this point, and are planning to do further research based on this first survey, we deemed the final version consisting of 24 items as sufficient. It is structured as follows: The heart of the questionnaire is made up out of 18 items concerning the different dimensions and factors mentioned in the research model (Figure 2.2).
15 of 18 items (Appendix 2.6) are statements equipped with a seven-point Likert-type scale (Likert, 1932), ranging from (1) to (7), where (1) means "strongly disagree" and (7) "strongly agree". The decision to use a seven-point Likert-type scale is founded on the chosen methods of statistical analysis: Spearman-Rho correlation for identifying interrelationship and Mann-Whitney U test for country differences. Most items are only shown to participants currently using an activity tracker. Other participants are asked for their reason(s) to discontinue usage.

The questionnaire contains, apart from these items, also socio-demographical questions and background information such as: place of residence, type of activity tracker, level of fitness (1-7), level of health (1-7), gender and age. Finally, there is space for further remarks by the participants. For the first step of our research, we only concentrate on the place of residence based on the socio-demographical and background information.

The questionnaire was pretested by nine German and English native speakers and distributed after the necessary corrections. Distribution took place mainly over social media channels (e.g. Facebook, Twitter and Reddit). On Facebook, the distribution took place mainly in fitness and activity related topic groups with different amounts of members, in both German and English language groups. As the posts in groups lose novelty rapidly, reposting was necessary. Apart from social media, the survey was distributed via mailing lists of universities and social messaging services (WhatsApp) to distribute it between individuals who use or did use an activity tracker. The participation was voluntary without any incentives and time limits. The distribution time was March 25, 2017 to June 08, 2017 and overall we reached 975 participants. After checking and cleaning the survey data, 803 participants, who successfully took part until the end of the questionnaire, were left.

2.4 Results

In the following section, the results of the survey will be presented. Overall, 674 participants were currently using an activity tracker, while 129 participants did not (anymore).

2.4.1 RQ1a: What strengths and weaknesses are recognized by the participants (based on perceived service quality and acceptance) concerning activity trackers?

The results of the present study Figure 2.3 demonstrate that activity trackers are received very positively. Brackets include the median value. The perceived service quality of activity trackers is generally high. Furthermore, the participants strongly agree (7) that their trackers are easy to use and that the use of them is fun (7). Participants confirmed that their trackers are useful for the improvement of health status and their fitness level (6). Based on the prompted aspect *Trust*, the respondents confirm that they judge the provider of their trackers as trustworthy and do not fear the company might be abusing the tracked data (5). Fitbit enables the user to collect badges or to take part in challenges. The participants somewhat agree that these kinds of gamified elements make them feel rewarded (5). All in all, no deficits were recognized regarding the perceived service quality, as the majority of participants agreed, to varying extents to all statements. The acceptance of activity trackers (D3), was rated related to the items *Impact* (6) and *Dissemination* (7) very positively, too. Many participants confirm a positive change in their behavior, for example, being more active (take more steps, walk an extra round, and so on). Furthermore, participants felt, that using activity trackers is improving their wellbeing. Users of an activity tracker strongly agree that they would recommend the tracker to friends and other family members – indeed, a majority of our respondents seems to be convinced by the functionality of their wearables and is satisfied. Another interesting result, not recognizable as a weakness, is the low agreement on *Enforcement* (1), *Group Pressure* (1) and *Contagion* (3).

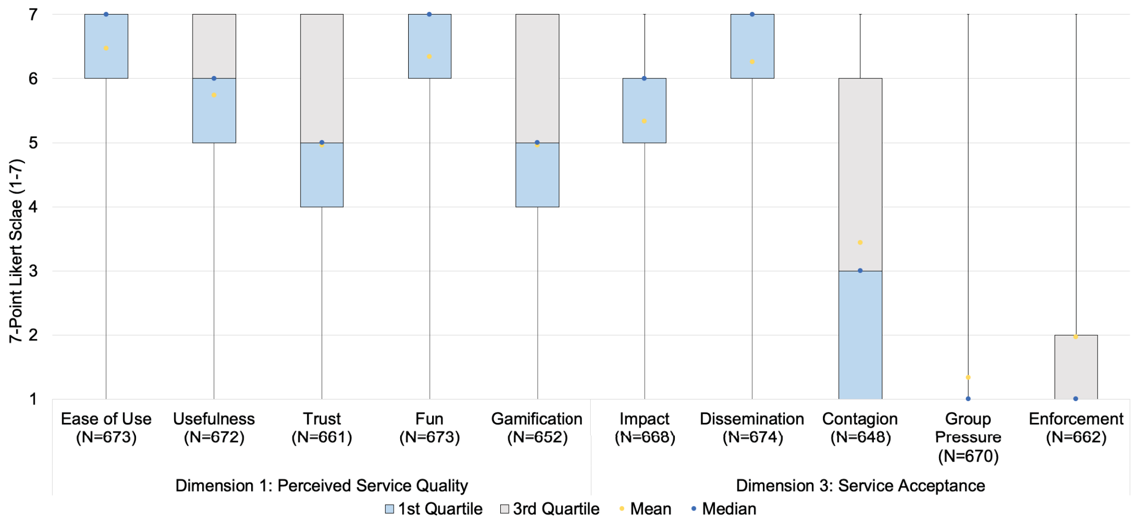

Figure 2.3: General agreement on perceived service quality and acceptance of activity trackers

2.4.2 RQ1b: How do perceived service quality and acceptance of activity trackers influence each other?

The results show that different items of the two dimensions (D1 and D3) correlate not only both, weakly and strongly, but negatively as well as positively, too (Table 2.1). The item *Ease of Use* correlates highly significant and positively with the items *Usefulness* (+.297***), *Trust* (+.194***), *Fun* (+.376***), *Gamification* (+.230***), *Impact* (+.295***) and *Dissemination* (+.314***). As the values are highly significant, the strength of the correlations is rather weak. Beside this item of Dimension 1, the item *Usefulness* correlates more highly and positively with *Fun* (+.488***) and *Impact* (+.673***). In both cases the correlation is highly significant. Furthermore, *Usefulness* and *Gamification* positively correlate with each other (+.475***). *Gamification* correlates more highly and positively with the items *Impact* (+.507***), *Dissemination* (+.441***) and *Usefulness* (+.475***). The fact that participants trust in the provider of their activity trackers to not abuse their data, correlates positively and significantly, but weakly with the items *Fun* (+.218***), *Gamification* (+.217***), *Impact* (+.254***) and *Dissemination* (+.262***). In the last case, the correlation between *Trust* and *Enforcement* is not only very small but only lowly significant as well (+.080*). It is very noticeable that the item *Dissemination* is the second item that has a high correlation with another item, here *Impact* (+.629***) and vice versa. Based on social aspects, Table 2.1 shows that there is a highly significant and weakly positive correlation between *Contagion* and *Gamification* (+.203***) and *Contagion* and *Enforcement* (+.314***). *Group Pressure and Enforcement* correlate positively and highly significant as well (+.466***). A negative correlation based on Table 2.1: *Fun* correlates highly significant and negatively with *Group Pressure* (-.219***).

Table 2.1: Bivariate rank correlation (Spearman's rho) between perceived service quality (Dimension 1), and service acceptance (Dimension 3) of activity trackers; p<.05*; p<.01**; p<.001***. The Correlation Coefficiant (CC) is done for the following categories Ease of Use = x_1, Usefulness = x_2, Trust = x_3, Fun = x_4, Gamification = x_5, Impact = x_6, Dissemination = x_7, Contagion = x_8, Group Pressure = x_9 and Enforcement = x_{10}

			Dimension 1					Dimension 3				
			x_1	x_2	x_3	x_4	x_5	x_6	x_7	x_8	x_9	x_{10}
Dimension 1	x_1	CC	1									
		N	673									
	x_2	CC	**+.297***	1								
		N	672	672								
	x_3	CC	**+.194***	**+.272***	1							
		N	661	660	661							
	x_4	CC	**+.376***	**+.488***	**+.218***	1						
		N	673	672	661	673						
	x_5	CC	**+.230***	**+.475***	**+.217***	**+.370***	1					
		N	652	651	643	652	652					
Dimension 3	x_6	CC	**+.295***	**+.673***	**+.254***	**+.496***	**+.507***	1				
		N	668	667	656	668	649	668				
	x_7	CC	**+.314***	**+.557***	**+.262***	**+.588***	**+.441***	**+.629***	1			
		N	673	672	661	673	652	668	674			
	x_8	CC	+.070	**+.144***	+.039	**+.086***	**+.203***	**+.174***	**+.107****	1		
		N	648	647	637	648	628	644	648	648		
	x_9	CC	**-.174***	**-.118****	-.036	**-.219***	-.010	**-.076***	**-.189***	**+.262***	1	
		N	670	669	658	670	650	666	670	647	670	
	x_{10}	CC	-.072	**+.094***	**+.080***	-.062	**+.183***	**+.138***	+.034	**+.314***	**+.466***	1
		N	662	661	650	662	644	658	662	639	661	662

2.4.3 RQ2: Do German participants' opinions differ from US participants', based on the agreement on perceived service quality and acceptance, regarding activity trackers?

This research question was further examined with the Mann-Whitney U test (MWU) to find out if there exists a significant difference between German and US participants related to their agreement on perceived service quality and service acceptance. The generally used statistical method for this purpose is the t-test, but this was not possible, as our data is not normally distributed. Therefore, we chose this method based on the characteristics of our data as the items are on an ordinal scale and not normally distributed.

Figure 2.4 shows among others, the median of the agreement on the specific items based on the country-specific perceived service quality. Related to two items, US participants tend to agree more than German participants. While German participants somewhat agree (5), US participants agree much more (6) that they trust the provider of their activity tracker. This difference is highly significant. Even the 3rd quartile of factor *Trust* is by US participants at the value of 7 the 3rd quartile related to German participants at the value of 6. In general, the strength of agreement differentiates on different shapes based on the 7-point Likert scale. US participants again agree a bit more (6) that they feel rewarded by functions such as the collection of badges, taking part in challenges or to improve their ranking, than German participants (5). Interestingly, the agreement related to the factor *Fun* differed, too. German participants tend to have more fun while using their activity tracker (7) than US participants (6).

Figure 2.5 shows the agreement on the specific items based on country-specific acceptance of an activity tracker. A very highly significance (***) is recognizable with items *Group Pressure* and *Enforcement*. The country-specific differences based on *Contagion* is weakly significant (*). Conspicuously, US and German participants totally disagree that the feel forced to use an activity tracker. But, the significant difference based on the tendency that US participants tend to disagree less (3rd quartile). Interestingly, US participants tend to agree more often that they feel encouraged by their environment to use an activity tracker.

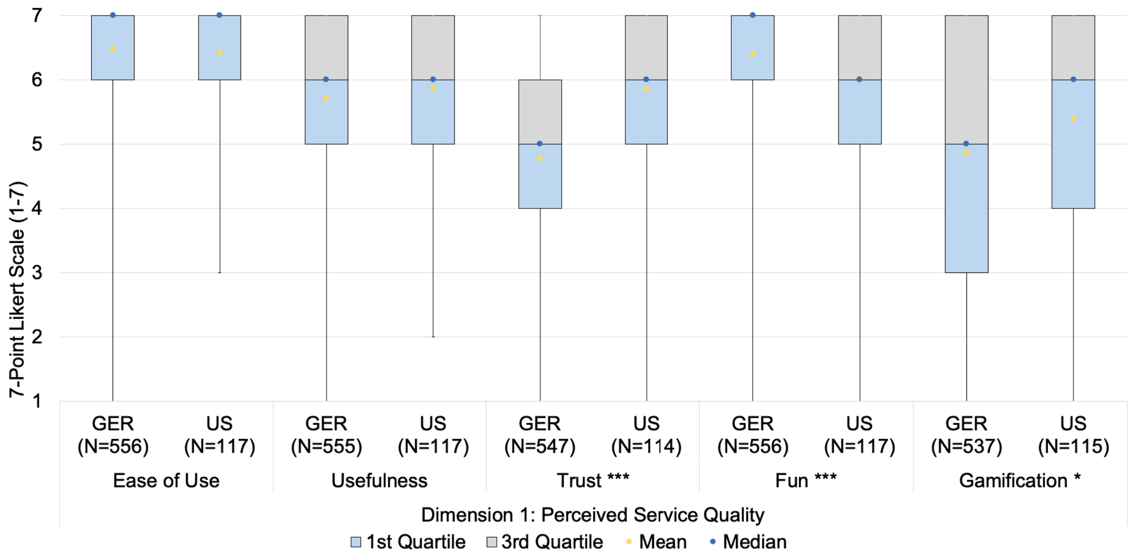

Figure 2.4: Country-specific agreements on perceived service quality and its significance (p<.05*; p<.01**; p<.001***) according to Mann-Whitney U test

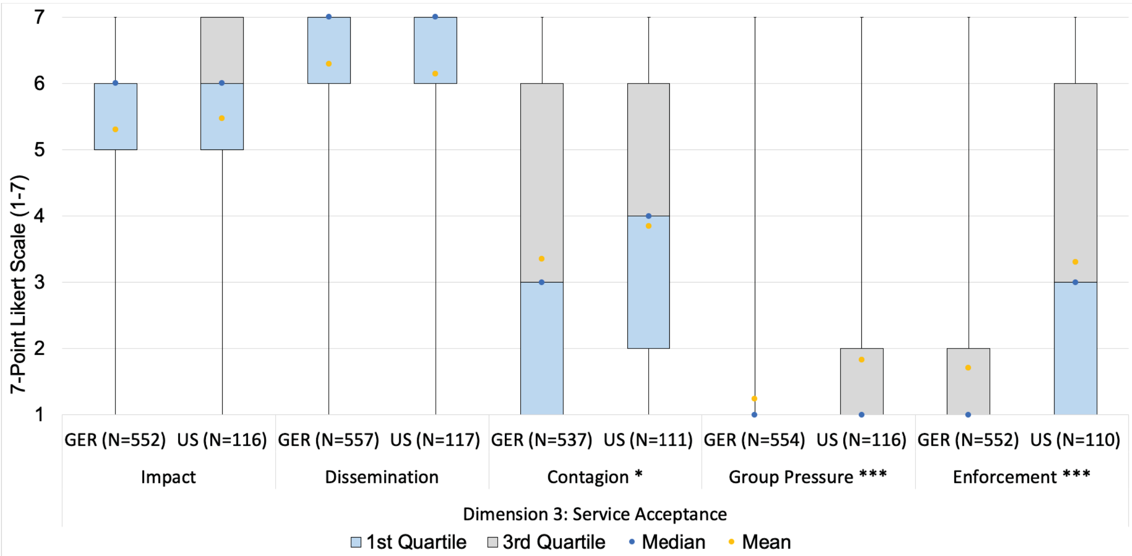

Figure 2.5: Country-specific agreements on service acceptance and its significance (p<.05*; p<.01**; p<.001***) according to Mann-Whitney U test

2.4.4 RQ3: What are country-specific user opinions and concerns on sharing activity data with health insurance and receiving rewards in return?

Table 2.2 shows that there are country-specific user differences on the agreement based on those two aspects. Especially the differences between German and US participants based on the reduction of medical fees by using an activity tracker is highly significant. German participants do not hope to save medical expenses in the present or future as much as US participants. The differences based on the agreement that health insurance funds should support users with tracked activities, are also significant. US users disagree less than German users and tend to agree with support from health insurance funds more in some cases.

Table 2.2: Country-specific differences ($p<.05$*; $p<.01$**; $p<.001$***) based on the agreement of getting support by health insurance funds and reducing medical fees by using activity trackers (scale: 1 (Strongly Disagree) – 7 (Strongly Agree))

		Mdn	1st Q.	3rd Q.	Mean	Std.	Sig.
Support of Health Insurance Funds	GER (N=538)	5	2	7	4.4963	2.24334	*
	US (N=105)	6	4	7	5.0190	2.01905	
Reduce Medical Fees	GER (N=541)	5	2	6	4.2921	2.11776	***
	US (N=117)	6	5	7	5.8547	1.35992	

2.5 Discussion

We presented an exploratory study regarding the adoption, impact, use and diffusion of activity trackers. We also identified issues, as the participation of health insurance funds, as well as country-specific differences. As previous findings are mostly based on a small size of participants or on qualitative interviews, a quantitative study, using an online questionnaire, was pursued. Activity trackers have become an interesting research subject and the use as well as the effects of this novel information system should be investigated thoroughly. Our study serves as another window to an understanding of the processes surrounding activity trackers. As the results show the simplicity of a system (here the use of the activity tracker) supports other aspects of the perceived service quality but also the acceptance of a service. A system that is easy to use and fun makes it easier to become more fit and healthy. Based on the results we could sum up that the more the service is perceived as easy to use, the more people get fun to use it and the more people disseminate the service to friends and families. Their willingness to disseminate activity trackers is assured by the perceived impact, too. The more people recognize that the activity tracker changes their behavior in a positive way, the more they will recommend the service to friends and family members. Especially for people who are not used to having a regular fitness schedule, actigraphs are used to support and facilitate the formation of new habits. In some cases, users need to be challenged to keep motivated. Feeling motivated is closely related to gamification. Gamification elements, such as rewards, challenges and rankings, are tools of motivation themselves but also an additional reason to invite friends to take part. On the other side, especially, if friends or family members are talking positively and excited about challenges and goals, the wish to take part oneself becomes stronger. New and successfully tackled challenges are fun and could improve self-awareness. Otherwise, people might lose interest in using their tracker, if they do not feel entertained or challenged. In the questionnaire, 5 users reported this as well. Other reasons for the discontinuance ("Opting-Out") of using activity trackers are faulty or damaged hardware (mentioned 10 times in the survey) and trackers that needed to be charged far too often (mentioned 7 times) or that were too expensive (6 times). 4 participants simply stopped tracking because the wristband felt uncomfortable while sleeping or working.

As activity trackers are said to enable the possibility to change behavior and improve wellbeing, it is necessary to test whether this is really true. If someone buys an activity tracker, and does not recognize any changes, then there could be two possible failure sources: The functionalities of the device missed or the user does not really use it as intended. Our results show, however, that our participants recognize their devices as useful and confirm an improvement of fitness level and health status. Additionally, the correlations of RQ1b shows that the more participants realize an improvement of their own health and fitness, the more they are having fun using the tracker and reverse.

In today's world, collecting all kinds of data via ICT is a given and has become a task of high importance for many institutions. But besides the fear of data abuse based on other services, the participants of this study do not mistrust providers in this area. In contrary, they somewhat agree that medical funds should support and reward the process of becoming more active by getting access to tracked data. In Germany, there are some medical funds who already give rewards if you buy an activity tracker or track steps with an app (AOK Plus, n.d.). Furthermore, the use of services can also depend on the social environment, as one would assume. But this research shows that most users are not being motivated by group pressure.

All in all, there are a lot of positive and highly significant correlations in the areas we examined. We can already see that the success of managing and improving personal health and fitness levels by using activity trackers is intermeshed with different aspects. If I recognize advantages by feeling better or by changing my behavior in a positive way, I also am more motivated to keep going on and reversed. Gamification may be seen to motivate a positive change in perceptions about usefulness and impact. This may indicate that people who feel rewarded by badges and rankings may also view the technology as useful and beneficial. Or if I really change my behavior, a typical example, I choose the stairs and not the elevator, I will recognize advantages in turn – so the device is used for improving user's fitness level and health status. And in the end, it is undeniable that all these positive aspects influence the willingness to disseminate activity trackers. Why should satisfied and motivated people not recommend their activity tracker?

Besides the mentioned positive correlations there exist negative correlations, too.*Dissemination* correlates weak but negatively highly significant with *Group Pressure*. *Group Pressure* may be seen as demotivation. Nevertheless, in combination with the item *Enforcement* it is recognizable that the more people notice that friends or colleagues are taking part in challenges together, the more people feel the wish to use an activity tracker, too. This seems paradoxical but could indicate that users' perception conflates between enforcement and group pressure sometimes. Especially because often communities at work or school are also social groups capable of applying group pressure.

Besides, effects or agreement based on different aspect could be country-specific. This could lead to different developments in the mentioned area of health insurance, depending on culture and other socio-demographical backgrounds. Therefore, the results show that US participants agreed more on reducing medical fees by using activity trackers. The reason for this result could be the different medical care systems. This opens up a new area of research, not only health information systems could improve or support the management of health insurance in any way, but the integration of medical funds or the integration of the medical care system could change completely. Another question is connected to the different kinds of 'Group Pressure': Is this really not an issue or are users simply not aware or not willing to admit being influenced by others? In our case, US participants tend to disagree less than German users, related to enforcement and contagion. For one example, in the United States, Oral Roberts University in Tulsa requires their students to buy and use an activity tracker.

Clearly, some propositions offered by the collected data are not entirely unique as the results given above prove that some aspects of the previous research are confirmed by many participants. However, we submit that the contribution of our paper rests on two relatively new areas: country-specific characteristics and external factors such as medical funds and the possibility to reduce medical fees. In the future, we want to try to get more American and international participants, as it seems that there is another perception of using and integrating activity trackers.

What is the right way to improve wellbeing, fitness and health? Should we start wearing actigraphs in preschools, schools and universities to educate pupils and to develop an awareness on how to improve health and fitness level? Previous studies show that interviews with users allow a deeper understanding of the circumstances and could help to identify problems and the potential of subjective feelings of wellbeing.

Our research has some limitations. We feel that our study emphasizes the need for more in-depth research on aspects that are going beyond the questions of this study. There is much more research potential if we concentrate on external and social-demographic aspects. Furthermore, a comparison between completely different cultural backgrounds, for example, Asian countries and Western countries, could be interesting, too.

Based on the aspect of external factors, such as medical healthcare funds and the reduction of medical cost, in-depth surveys and interviews would be the next step in the future, also to compare the perception of medical healthcare funds and activity tracker users based on this topic. Furthermore, our empirical data represent different age groups. Therefore, another future project could be the analysis of differences between different generations (Baby boomers, Generation X, Generation Y, Generation Z) (Lins, Fietkiewicz, & Lutz, 2016).

Finally, potential future research based on this data could also be the fitness level and health status background. Users that are not healthy could probably be more motivated by the support of medical healthcare funds than very active people.

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2.6 Appendix

Item		Item	7-Point Likert Scale	Question/Indicator
1				Please select your place of residence:
2				Do you currently use an activity tracker?
3			x	By sharing fitness activities with my health insurance (documented by my activity tracker) I should be eligible for finical support, for example by lowering health insurance contributions.
4			x	By being active I hope to save medical expenses in the present or future (for medicine or medical treatment).
5	D1: Perceived Service Quality	Easy to Use	x	My activity tracker is easy to use.
6		Usefulness	x	By sharing fitness activities with my health insurance (documented by my activity tracker) I should be eligible for finical support, for example by lowering health insurance contributions.
7			x	My activity tracker is useful for the improvement of my health status.
8		Trust	x	I am trusting the provider of my activity tracker to refrain from abusing my data in any way.
9		Fun	x	It is fun to use my activity tracker.
10		Gamification	x	I feel rewarded by functions such as the collection of badges, taking part in challenges or to check my ranking.
11	D3: Service Acceptance	Impact	x	Ever since I am using my activity tracker, I am feeling better.
12			x	Ever since I am using my activity tracker, I absolutely do not want to abstain from using it.
13			x	My activity tracker changed my behavior (I take the stairs more often or go an extra round).
14		Dissemination	x	I would recommend the activity tracker to others.
15		Contagion	x	Friends, family members or colleagues had an activity tracker. Somehow it was contagious and I bought an activity tracker, too.
16		Group Pressure	x	I feel forced to use an activity tracker by people in my environment (e.g. school class, colleagues, family members).
17		Enforcement	x	During school, university or on the job I feel encouraged to use an activity tracker. For example, to go take part in competitions or activities (such as collecting steps together during break).
18				Why are you currently not using an activity tracker?

3 Health Metrics and Information Behavior: How Users Estimate and Use Self-Quantifying Activity and Health Information

Ilhan, A. (2020). Health metrics and information behavior: How users estimate and use self-quantifying activity and health information. *Journal of Information Science Theory and Practice, 8*(3), 47–63. https://doi.org/10.1633/JISTaP.2020.8.3.4

Abstract *This study focuses on users of activity tracking technologies and their related information behavior. How useful is the provided information by the trackers? Do users understand all information and explanations? We conducted a web-based survey. All in all, 631 users of a tracking device filled out the survey. From the perspective of information science, this investigation aims to analyze information needs considering different types of the provided information by activity tracking technologies. Are users satisfied by using the information on their steps, heart rates, and sleep duration? How do users assess readability about heart rate zones and sleep stages? Additionally, we investigated if users understand how to reflect on and adapt their health behavior based on the received explanations. According to the results, users mainly agree that the received information (raw data as well as – to a lesser extent – aggregated data in the form of corresponding diagrams) is useful, that the explanations are easy to understand, and that they know how to use this obtained information. This investigation enables an in-depth insight into how users are applying the self-quantifying activity and health information and which information needs are satisfied.*

3.1 Introduction

With upcoming activity tracking technologies, self-knowledge through collected data (also known as self-quantification, self- tracking) rapidly increases in the domain of health and fitness, making users' abilities to self-regulate more and more important. According to Lupton (2016, p. 6), "digital data about people's lives are also vital in their effects [...] they have begun to play a significant role in influencing people's behaviors..." Users of these technologies get the possibility and authority to quantify, monitor, and analyze the collected data by using activity tracking technologies anywhere and anytime (Lupton, 2014, p. 77). Activity tracking technologies enable users to collect fitness and health-related metrics such as counted steps, burned calories, heart rate, and sleep cycles. Here, the term *activity tracking technology* refers to activity trackers, also called fitness trackers (e.g., wearables of Fitbit, Xiaomi, Garmin), smartwatches (e.g., Apple Watch, Samsung Galaxy Watch), and mobile applications (e.g., Strava). With all forms, it is possible to digitally log health and fitness-related metrics. While some activity trackers enable the possibility to automatically track health and fitness-related metrics with less effort, some mobile applications need the data to be manually logged by users, such as nutrition applications (Rooksby, Rost, Morrison, & Chalmers, 2014).

Especially in the human-computer interaction discipline, activity tracking technologies are investigated as a subtype of the so-called personal informatics systems. According to Li, Dey, and Forlizzi (2010), personal informatics systems enable people to receive information about themselves towards self-reflecting and developing self-knowledge about different personal areas. Furthermore, Li et al. (2010) differentiate between a system-driven and user-driven personal informatics system. Following the definition by Li et al. (2010), in this investigation activity tracking technologies will be characterized as a 'mixed' personal informatics system. Even if the activity trackers are mainly system-driven (collecting data through sensors and pedometers, and visualizing data automatically), users have yet the possibility to choose which of the functionalities they would like to use and to change default goals.

By now, activity tracking technologies draw the interest of different research fields (e.g., computer science, human-computer interaction, information science, system sciences, engineering, medicine, and social sciences). All in all, the publications indexed by Scopus increased from about 100 in 2015 to more than 450 in 2019 (Figure 3.1a). Drawing on the systematic literature review of Shin et al. (2019), all publications after 2012 were included.

In particular, the research field of medicine and healthcare is interested in investigations about activity tracking technologies' accuracy, reliability, feasibility, and validity (e.g., Diaz et al., 2015; Evenson, Goto, & Furberg, 2015; Martin et al., 2015; Rosenberger, Buman, Haskell, McConnell, & Carstensen, 2016). Besides this, to what extent and why users of activity tracking technologies engage, adapt, and use these devices was investigated as well (e.g., Fritz, Huang, Murphy, & Zimmermann, 2014; Gouveia, Karapanos, & Hassenzahl, 2015; Lyall & Robards, 2018; Nelson, Verhagen, & Noordzij, 2016; Rooksby et al., 2014). Additionally, there are also studies that investigated barriers and reasons why users stop using one or find workarounds (e.g., Harrison, Marshall, Bianchi-Berthouze, & Bird, 2015; Shih, Han, Poole, Rosson, & Carroll, 2015). Even if investigations show useful insights such as why and how participants use activity trackers, studies focusing on the use of information are yet rare. Mostly the emphasis is set on the functionalities and design of a system. To the best of our knowledge, there are only a few studies which are mainly focused on the users and interaction and engagement with the collected data, which reflects a major aspect of information science (Feng & Agosto, 2017, 2019a, 2019b; Feng, Li, & Agosto, 2017).

Particularly concerning the characteristics of personal informatics systems and self-quantification, we assume that the information provided by these technologies might play a crucial role in reflecting on and evaluating behavior and in learning more about oneself. Activity tracking technologies are mainly system-driven, which makes it crucial to investigate if the provided information is easy to use and easy to understand, as well as necessary in the eyes of the users. Since activity tracking technologies allow interpretation and evaluation, their correct understanding depends on the users, their knowledge, and their skills. Therefore, to better understand the use of the information, it is also crucial to understand if people can transform the provided information into actions, which in turn is dependent on the usefulness of the provided information. The perceived usefulness of information is crucial regarding health information literacy. As Stock and Stock (2013) already mentioned, users are differently engaging with information systems and the use of information systems depends on their level of information literacy. The more that users are information literate, the more they are able to interact with information systems. And the more information systems are usable, the more users will interact with them.

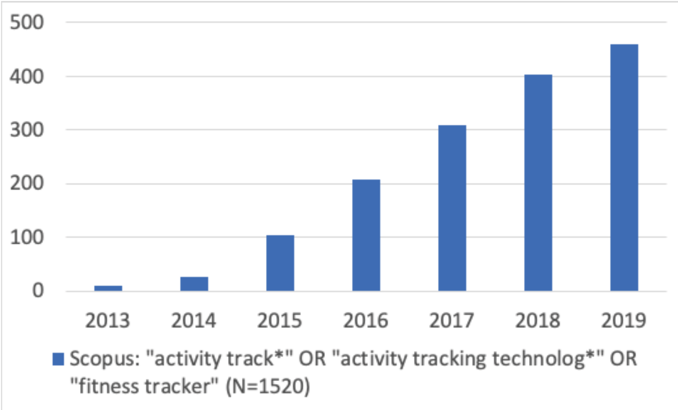
Therefore, apart from the system-side provision of information by an activity tracking device, this investigation aims to gather further useful insights from the perspective of information science, drawing on the subfield of information behavior.

Health information behavior and the tracking of someone's activity is a rather new topic in information science. For many scientists, information behavior is more than searching and finding information, as for example information production and consumption behavior on information services (Friedländer, 2017a, 2017b; Scheibe, Fietkiewicz, & Stock, 2016). According to Wilson (2000, p. 49), "[i]nformation [b]ehavior is the totality of human behavior in relation to sources and channels of information, including both active and passive information seeking, and information use." According to (Pingo & Narayan, 2019, p. 506), "[t]he understanding of how people make meaning out of fitness tracker data is a vital aspect of their information seeking, which provides an important and interesting perspective for information behaviour research." Activity tracking technologies offer visualized data (graphs) and explanations on sleep cycles and heart rate zones. Is the provided information necessary and useful and, even more importantly, are users able to reflect on and adapt their behavior based on these explanations? According to Stock and Stock (2013), characteristics such as recognizing an information need, the ability to evaluate information, and the synthesis of previous and new obtained information is assigned to the concept of information literacy.

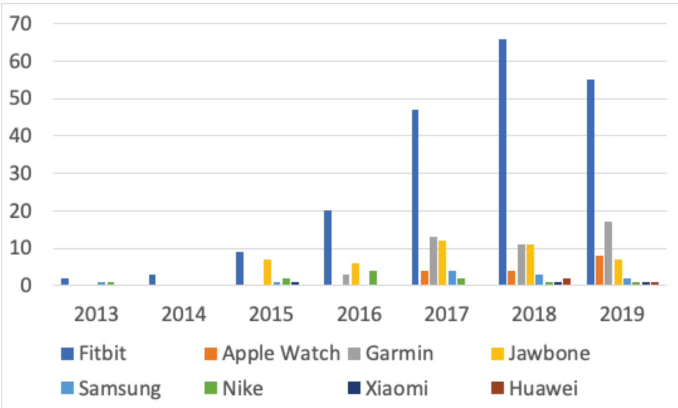
Information behavior depends on the context. For this study, the context is found in activity tracking devices and applications. However, research on information behavior on activity tracking can be said to be in a nascent stage.

To restrict and therefore enable deeper insights into results as each device has specific, individually designed, and integrated functionality and explanations, this study focuses on wearables provided by Fitbit. The search in the database Scopus showed Fitbit is the most investigated wearable (Figure 3.1b). Fitbit was founded in 2007 in San Francisco and develops wireless wearable technology to track health and fitness-related data. Fitbit has more than 27 million active users worldwide and shipped five million devices worldwide in the last quarter of 2018 (Liu, Oct. 17, 2019).

This investigation aims to derive implications for future research in many ways: To what extent is the need on activity and health information satisfied with data provided by activity tracking technologies? Are there any ambiguities regarding the understanding of how to interpret and reflect collected data? Is the provided information necessary and useful? The paper will give a consolidated theoretical background covering the concept of *information behavior* and an insight into investigations on activity trackers. The Methods section reveals the developed web-based survey, its distribution, and the used quantitative approaches. This is followed by answering the research questions (RQs) and a discussion of the findings and implications.



(a)



(b)

Figure 3.1: (a) Time series of publications on "activity tracking" 2013-2019. (b) Studied activity tracking devices. Source: Scopus (May 3, 2020); search in article titles, abstract, and keywords.

3.2 Literature Review

In recent years there has been growing interest in understanding why and how users engage with activity tracking technologies to better understand how to design and develop wearables. Rooksby et al. (2014) revealed that reasons for using activity trackers are to track walking (e.g., developing awareness), physical exercise, food and drink (e.g., because of being interested in losing or maintaining weight), weight, size, and sleep patterns. Further, investigations on activity tracking technologies also enable users to understand how activity tracking technologies change users' information practices (Pingo & Narayan, 2019). Even if activity tracking technologies have much functionality in common, they are not equally important as it depends on the intended goals. Furthermore, activity tracking technologies might not be only crucial regarding gaining awareness of somebody else's activity level, but also "to provide structure and motivation to people who feel incapable of implementing their intention of exercising without support" (Gouveia et al., 2015, p. 1305).

Gouveia et al. (2015) developed a mobile application called *Habito* to track physical activity. They explain that in order to better determine the success or failure of behavior change, it is crucial to investigate to what extent users engage with specific features. They revealed that the motivation to engage with an activity tracker depends on the readiness of users to be physically more active. The authors point out that most of their participants were in a short engagement phase (less than 10 sec.), where they only screen values instead of intensive reviewing and engaging with information. They conclude that even if behavior change is characterized as gaining valuable knowledge about oneself, users are not interested in reflecting on past tracked data and, therefore, in changing their behavior (Gouveia et al., 2015). Users of activity tracking technologies apply the devices with different goals, some reasons being "directive tracking [e.g., goal-driven], documentary tracking [e.g., awareness, reflection, confirmation], diagnostic tracking [e.g., identification of connections between things, searching for an answer for situations (headache, bad sleep), analyzing data], collecting rewards, and fetishised tracking [purer interest in gadgets and technology]" (Rooksby et al., 2014, p. 1167). Lyall and Robards (2018) investigated how users of activity tracking technologies engage with tracked data by conducting interviews. They question how the interviewees use their data and create an added value. They provide three roles which characterize activity tracking technologies, namely tool (to reach a goal, to raising awareness, to monitor), toy (playful gadget), and tutor (guiding towards a healthier lifestyle). Additionally, activity tracking technologies are also used to monitor progress and one's own goals, to decrease the level of intensity (Patel & O'Kane, 2015), and to control one's health (Gowin et al., 2019).

There are investigations which studied the impact of wearables on users' behavior (Fritz et al., 2014; Ilhan & Henkel, 2018). Fritz et al. (2014) investigated long-term users and how wearables influenced their physical activity. The study highlights that long-term users developed an awareness of their physical activity regarding different settings (routine and non-routine activities). Participants of the study by Fritz et al. (2014) also indicated that even if they use their wearable, they pay less attention to the data as they already know their behavior patterns. Gouveia et al. (2015, p. 1309) come as well to the conclusion that "when individuals become more self-reliant, use is more and more marked by brief, reassurance-seeking, glance interactions." Ultimately, activity tracking technologies can impact users' behavior by, for example, taking more steps instead of an elevator to receive more steps (Fritz et al., 2014; Ilhan & Henkel, 2018).

A downside of activity tracking technologies exists to the effect that self-quantification might lead to obsessive measuring. Fritz et al. (2014) point out that their study revealed that participants focus on numerical goals and data to receive credits through tracking. Activities that might not be able to be tracked by devices were less attractive, and a user avoids them or does other activities where they might receive more credits Fritz et al. (2014); Harrison et al.

(2015). Lyall and Robards (2018, p. 115) affirm this downside as well by explaining that the "potential problem here is that self-tracking data displays may dictate meaning and, by extension, define the human actions they record."

Summarized, several studies have been carried out to understand why users use activity tracking technologies and how. We agree with Feng et al. (2017) as well as Feng and Agosto (2019a, 2019b) that the personal information management (PIM) of activity tracking users was rarely investigated. They draw on the framework of PIM (Jones, 2007, 2012) and investigated the personal health information management of users of activity tracking technologies (Feng & Agosto, 2019a, 2019b; Feng et al., 2017). The results show that health and fitness-related needs such as achieving a better performance require an information need (Feng & Agosto, 2019a). Feng and Agosto (2017) surveyed users of activity tracking technologies to investigate how users engage with the personal health information. They confirmed that users who used the device for the long term would continue to use it, similar to the results of Gouveia et al. (2015). Feng and Agosto (2017) also underline that 74% of the participants use their tracker almost all the time. Feng et al. (2017) showed that steps, distance, calories, sleep, and heart rate were mainly provided by activity tracking technologies (more than by half of the users' activity tracker). According to Feng et al. (2017), the provided information includes different types of data: raw data directly generated by activity tracker sensors, as well as more complex and processed information such as routes or calories burnt during an exercise. During the study by Feng et al. (2017) participants (current users) mainly agreed that the charts, tables, and timelines of activity tracking technologies are clearly presented. The interviews conducted by Pingo and Narayan (2019) showed that the visualized data were easy to use as well.

Nevertheless, as people bring along different requirements (needs), experience, and knowledge, users' contexts and the role that information plays in this situation is decisive (Lyall & Robards, 2018). Therefore, experiences regarding the information provided by activity tracking technologies might be perceived differently. Especially, if users of activity tracking technologies see the raw data or diagrams and explanation for the first time it might affect the experience as well. Furthermore, a study conducted by Maher, Ryan, Ambrosi, and Edney (2017) revealed that three out of 37 former users and seven out of 200 current users indicated that they have problems with interpreting collected and provided data by their activity tracking devices. Further, two former users explained that it was difficult to understand the provided information by activity tracking technologies and that the information was not important. Furthermore, even if activity tracking technologies enable users to gain self-knowledge and to self-regulate, investigations in the past also revealed challenges. Zhang, Schaub, Feng, and Sadeh (2019) stress that activity tracking technologies do not give specific suggestions on how to improve poor sleep. Further, Liang, Ploderer, and Chapa-Martell (2017) investigated Fitbit users and showed that the definition on how the sleep metrics are measured is not reasonable. Even if users might be able to gain self-awareness and monitor their tracked health and fitness-related metrics, these metrics might raise questions which are not answered by them.

Based on these narrowed insights, the study aims to investigate to what extent the different types of information provided by an activity tracking device enable users to achieve their needs and if they reflect on and adapt their behavior based on the provided information. For this purpose, the next section introduces the theoretical background of this investigation and frames the work.

3.3 Theoretical Background

This study draws on the concept of *information behavior* to better understand users' needs and how the information provided by wearables and mobile application supports the accomplishment of these needs. Information behavior (IB) reflects active as well as passive activities by people. According to Case and Given (2016, p. 6), IB also "includes the broader context of how individuals 'deal with' information in their lives, so accounts for situation, time, affect, culture, geography, and other contextual elements in understanding people's IB."

Wilson (2000) emphasizes that information behavior is made up of three sub-sets, namely information-seeking behavior, information searching behavior as a sub-set of information- seeking, and the information use behavior. Ultimately, "by information behaviour is meant those activities a person may engage in when identifying his or her own needs for information, searching for such information in any way, and using or transferring that information" (Wilson, 1999, p. 249). Investigations within the context of information science are mainly focusing on information searching behavior, "particularly concerned with the interactions between information user (with or without an intermediary) and computer-based information systems, of which information retrieval systems for textual data may be seen as one type" (Wilson, 1999, p. 263). Besides activities such as seeking and searching, the activity to use information does not only mean to apply information but also to ignore information (Case & Given, 2016). Overall, the concept of *information behavior* is a "nestled field" (Wilson, 1999, p. 263). Considering all the subsets and terms within the concept of information behavior it is important to define terms related to information behavior (Agarwal, 2018). According to Case and Given (2016), information need is the situation where an individual realizes that there exists a knowledge gap to reach a desired goal. In the context of information behavior, information-seeking describes "a conscious effort to acquire information in response to a need or gap in your knowledge" (Case & Given, 2016, p. 6). It is important to realize, while investigating or speaking about information behavior, that the concept of information behavior does not only consist of the seeking-behavior as people "may choose not to seek, or information may simply find them [...] before a person even realizes that they want to learn more" (Case & Given, 2016, p. 7).

Up to this point and building on (Case & Given, 2016), in this study we define information need as the knowledge gap to be able to reach desired goals. According to the previously introduced literature, we pre-define these needs as developing awareness, improvement, assessment, and identifying and interpreting differences and saliences of fitness and health- related activities. The question that arises here is, what is the information and the source and who is the actor?

According to Agarwal (2015, p. 4), an actor is defined as a "seeker, user or person who is looking for information or who finds information on something unexpectedly." In this case, the users of activity tracking devices are the actors, and we assume that they are using the wearables because they have a need, such as improving their health and fitness-related activities. For this need, it is crucial to know the current activity status. Therefore, there might exist a knowledge gap, like not knowing how much they are walking. Here the information need is understood as the desire to see the count of steps. Without knowing that, a user might not be able to improve the level of physical activity. Information use describes both the use of the information (Agarwal, 2015; Line, 1974) and also the ignoring (Case & Given, 2016). In this investigation, looking at the provided logged metrics and graphs is understood as using the information. We already defined information use, information need, and information-seeking, but we did not specify the term *information*. According to Case and Given (2016), there does not exist a homogenous understanding of information. Buckland (1991, p. 351) characterizes information by dividing it into three types: "Information-as-process" (e.g., informing someone), "Information-as-knowledge," and "Information-as- thing" (such as documents). According to Feng and Agosto (2019b), as the wearables produce the data, there is the speech of "information-as-thing." In information science, "we analyze information as data *and* meaning (knowledge) in context" (Stock & Stock, 2013, p. 22). Wearables provide data to their users; and the users give them meaning and gain knowledge in the context of fitness and health information.

The types of information provided by Fitbit are differentiated regarding their *richness* of information and complexity (Figure 3.2). *Type 1* is the solely visual displaying of a value like the actual heart rate, the number of steps, distance, amount of sleep hours, and so on. According to Feng et al. (2017), this type is also characterized as "raw data." *Type 2* describes provided information that is more detailed and offers more associated and aggregated values (e.g., time series, summarized workouts). *Type 3* offers explanations regarding the heart rate zones and sleep quality.

Especially regarding Information Type 3, we assume that users need to be able to understand how to reflect on and adapt the presented information and insights.

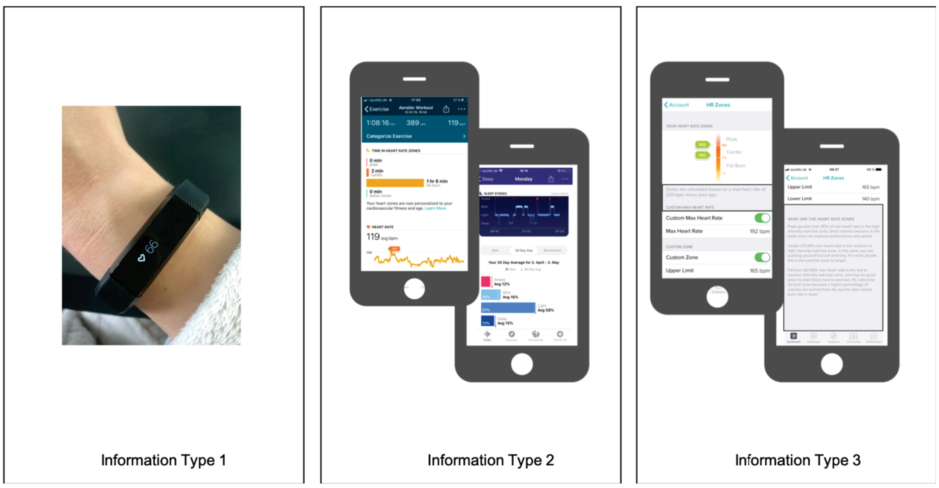


Figure 3.2: Information types provided by Fitbit: Raw data (Type 1), aggregated data (Type 2), and explanations (Type 3)

The information behavior of users can be influenced by the usefulness of provided information by information services (Stock & Stock, 2013). Users who might be more information literate easily use and understand the information as opposed to people who are lower information literate. Therefore, health information literacy enters the stage. According to our context, we apply the definition of *health information literacy* as activity tracking technologies track health and fitness-related metrics. Eriksson-Backa, Ek, Niemelä, and Huotari (2012, p. 84) state that "[a] related concept that describes health-related information behaviour, including needs, seeking and use of information related to health or medicine is *health information literacy* [...]." Health information literacy is defined, according to the Medical Library Association (2005, p. 1), as abilities to "recognize a health information need; identify likely information sources and use them to retrieve relevant information; assess the quality of the information and its applicability to a specific situation; and analyze, understand, and use the information to make good health decisions" (Hirvonen, Pyky, Korpelainen, & Huotari, 2015, p. 3). Why is this important for this study? According to Hirvonen, Huotari, Niemelä, and Korpelainen (2012), the health information behavior research on physical activity showed that information needs and information use increase with higher task complexities and levels of activities.

Based on the theoretical foundation and previous investigations on activity tracking technologies, this paper aims to answer overall three RQs. Based on the complexity of a need we assume that different needs require different types of information. For example, the need of interest or curiosity of knowing how many steps a user collected, what his or her actual heart rate is, or how many hours a user slept last night requires raw data (Information Type 1). On the contrary, complex activities such as getting to know which activities influence heart rate during a workout and, therefore, decisions on how to change a specific behavior require aggregated data (Type 2) and explanations (Type 3). Therefore, the first research question (RQ1) is formulated as follow:

RQ1: To What Extent Are Fitbit Users' Needs Satisfied by Using the Provided Information (Type 1 and Type 2)?

Here we aim to oppose the two information types, the raw data (Type 1) as well as the aggregated data (Type 2), to better understand if the provided information is differently useful and if the information is also equally used. Generally, the use of diagrams needs engagement with the application and might provide summarized data over a period, while Type 1 needs regularly only a look at the wearable and shows real-time information.

RQ2: How Do Fitbit Users Perceive the Readability of Explanations about Heart Rate Zones and Sleep Stages' Characteristics (Type 3)?

Fitbit provides explanations (Type 3). According to Nelson et al. (2016), the readability of information influences the engagement. Therefore, before we investigate if users can adapt and use that information (health information literacy), we wanted to examine the readability of this information (system-oriented).

RQ3: To What Extent Do Users Understand the Provided Explanations (Type 3) and How Do They Estimate Their Usefulness?

In the next step, we concentrate on the users and their use of explanations (Type 3). As Fitbit is using words and descriptions assigned to the health and fitness-related context, these explanations might not be self-explaining for users within the same context (e.g., seeing this explanation more frequently versus seeing them for the first time). Further, according to the health information behavior and health information literacy concept, users need to have the abilities to "...assess the quality of the information and its applicability to a specific situation; and analyze, understand, and use the information to make good health decisions" (Hirvonen et al., 2015, p. 3). Therefore, we investigate if users know how to use these explanations to reflect on and adapt their behavior or if they will do so in the future.

3.4 Methods

We conducted an explorative quantitative study in order to gain more insights from an information science perspective and constructed an online survey with the help of eSurveyCreator.com (Connaway & Radford, 2017). At the time of the survey, Fitbit's newest function, the calculated sleep value, was not available. We decided to concentrate on the features *steps* (this is a minimum that all activity trackers provide), the *heart rate*, and *sleep functions*. Screenshots of Fitbit's explanations contain information about the different sleep stages (light, deep, rapid eye movement [REM], awake) and heart rate zones (fat-burning, cardio-zone, maximum heart rate). For the screenshots included in the survey, Fitbit's permission was acquired. The screenshots of Fitbit's sleep stages' characteristics were only for participants visible whose activity tracker offers the tracking of the heart rate.

The survey consists of *four parts* (see Supplemental Materials or Appendix (3.8)). The *first part* includes demographics and background questions (e.g., usage duration, exercise level) to gain first insights into the characteristics of the sample. The *second part* represents the investigations' aim to understand the need for information to develop awareness, improve and assess health and fitness- related behavior, and identify and interpret differences and saliences and the information use (Type 1 and Type 2). The *third part* of the survey represents aspects that enable empowerment to change behavior positively by using Type 3. This part of the questionnaire includes readability statements adapted and modified from Nelson et al. (2016). Finally, the *fourth part* includes statements regarding health information behavior and the perceived usefulness and understandability of provided explanations. Those statements are connected with abilities assigned to the concept of health information literacy (such as being able to use, reflect on, or synthetize information). Therefore, this part mapped questions about reflecting on, adapting, and use of that information (Type 3), leaning on Eriksson-Backa et al. (2012) and the general definition of the Medical Library Association.

We segmented the *third* and *fourth part* of the survey into two parts—including users who already knew the explanations and users who saw the explanations for the first time during the survey.

The survey includes conditional questions to ensure that the participants of the survey only get questions based on the features they actually use. The survey also includes optional free-text fields to share further experiences. We developed two surveys, one in German and the other in English, which were distributed separately.

Before we distributed the survey, from March 28, 2019 until August 26, 2019, the questionnaire was pretested by six Fitbit users (two male and four female testers) and two volunteers for the translation. The language was slightly modified, and ambiguities were resolved. The questionnaire was distributed in diverse German and English-speaking health and fitness-related Facebook groups, Reddit, our own social network channels, universities (mailing-lists, face-to-face), and gyms. We did a convenience sample as it is not possible to reach all Fitbit users in the world. The convenience sample seems to be adequate for sharing the survey in Fitbit and fitness and health- related Facebook groups, and for other sources as they could include the target group. Therefore, the sample population was easy to contact. Participation was voluntary, and there were no payments or vouchers.

Data analysis was conducted with IBM Software SPSS Statistic 26, and variables as type string was coded into numerical values. Based on the variable 'usage duration' we created a new variable to summarize the characteristics into newbie (less than a week, 1-2 weeks, three weeks, a month), short-term (several months), medium-term (a year), and long-term (several years). Further, we grouped the birth cohorts into a new variable 'Generation' with Silver Surfers (born before 1960), Generation X (1960- 1979), Generation Y (1980-1995), and Generation Z (born after 1995) (Fietkiewicz, Lins, Baran, & Stock, 2016). Statements based on a Likert scale (here a 5-point Likert scale) and the variables 'exercise frequency,' 'usage duration,' and 'Generation' are ordinal, which is why we need to use nonparametric tests. As the data is mostly ordinally scaled, we apply the median (Mdn) and the interquartile range. We used the Mann-Whitney U test, a rank-based nonparametric test, to determine statistically significant differences between independent variables (with two characteristics) and dependent ordinal variables regarding the distribution of the answers (Laerd Statistics, 2018). For interpretation, lower mean ranks indicate lower values regarding the evaluation (Likert scale) and vice versa. The U test (via SPSS Statistics Legacy Dialogs) was used to determine whether the distribution of answers regarding the perceived readability differs between users who already knew these explanations and users who saw it for the first time (RQ2). Further, for answering RQ3, we conducted the U test for all statements assessing the perceived usefulness and understandability of the provided information except for the statements such as (I adapted my behavior vs. I will adapt my behavior) and (I reflected my behavior vs. I will reflect my behavior), as these activities are different. In the description of results, MR is the mean rank, U is the test statistic, z value is scaled to the standard normal distribution of the U-value, n is the number of participants, and p is the probability rejecting the null hypothesis (H_0), although it is true, thereby erroneously accepting the alternative hypothesis (H_1). The following significance levels were determined: p-value$\leq$0.05*, p-value$\leq$0.01**, p-value$\leq$0.001***.

All in all, 1,016 persons participated in the survey; finally, 631 valid cases were identified.

3.5 Results

Table 3.1 gives an insight into the sample's characteristics. The majority of the participants were female (88.1%), and most users were between 40 and 59 (37.7%) or between 24 and 39 (48.3%) years old. The majority of the participants answered that they are exercising 1-2 times (25.5%), or three or more times per week (38.5%). In conclusion, most participants in this sample were somewhat physically active, and most participants were long-term users. Furthermore, 85.3% are using their wearable throughout the whole day and night.

Table 3.1: Demographics and background of Fitbit users (N=631); Y, yes; N, no.

Variable		Value
Sex		
	Female	88.1%
	Male	11.4%
	I prefer not to say	0.3%
	Free text field	0.2%
Generations		
	Silver surfers (<1960)	7.8%
	Generation X (1960-1979)	37.7%
	Generation Y (1980-1995)	48.3%
	Generation Z (>1995)	6.2%
Exercise frequency		
	Never	4.0%
	Few times per year	2.2%
	Every few months	4.1%
	Once a month	3.2%
	Several times per month	8.7%
	1-2 times per week	25.5%
	3 or more times per week	38.5%
	Every day	13.2%
	I prefer not to say	0.6%
Since when have you been using your Fitbit?		
	Newbie (less than a week, 1-2 weeks, 3 weeks, a month)	6.8%
	Short-Term (several months)	20.8%
	Medium-Term (a year)	18.1%
	Long-Term (several years)	54.4%

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Variable		Value
How frequently do you wear your Fitbit?		
	Only while exercising	0.8%
	Only when I'm leaving the house	0.8%
	Throughout the whole day but not while sleeping	9.7%
	Throughout the whole day and night including sleeping	85.3%
	Irregularly	2.1%
	Free text field	1.4%
Steps		
	Use of raw data (Type 1)	N=631, (Y) 91.4%, (N) 8.6%
	Use of diagram (Type 2)	N=577, (Y) 71.1%, (N) 28.9%
Heart Rate		
	Feature heart rate tracking	N=631, (Y) 94.8%, (N) 5.2%
	Use of raw data (Type 1)	N=598, (Y) 67.2%, (N) 32.8%
	Use of diagram (Type 2)	N=402, (Y) 72.4%, (N) 27.6%
	Noticing explanation (Type 3)	N=402, (Y) 71.1%, (N) 28.9%
Sleep		
	Feature sleep tracking	N=631, (Y) 99.5%, (N) 0.5%
	Use of raw data (Type 1)	N=628, (Y) 75.5%, (N) 24.5%
	Use of diagram (Type 2)	N=474, (Y) 80.6%, (N) 19.4%
	Noticing explanation (Type 3)	N=459, (Y) 91.5%, (N) 8.5%

3.5.1 RQ1: To What Extent Are Fitbit Users' Needs Satisfied by Using the Provided Information (Type 1 and Type 2)?

Table 3.2 shows predefined needs, namely awareness, improvement, assessment, and identification/interpretation, and summarizes the evaluation of users' information needs and if the usage of provided information (Type 1 and Type 2) satisfies their information needs. Regarding the information need, Table 3.2 shows that users mainly agree that they are looking at the provided information (Type 1 and Type 2) because they want to gain awareness (e.g., to get information how many steps they walked, gaining awareness about routines, current heart rate while working or exercising, how long do they sleep, how did they sleep after exercising), to improve their health and fitness- related behavior (to get information about current heart rate to reduce or estimate if it is good, going to bed earlier, to take stairs more often, generally to walk more), and at least, to get information to be able to assess the tracked health and fitness- related metrics (e.g., did they walk a lot of steps, is their heart rate too low/high, was it a 'good' or 'bad' sleep). They also mainly agree that they are looking at the diagrams because they want to interpret and identify differences and saliences (Type 2).

Table 3.2 confirms that participants mainly agree that the use of information, both 'raw data' (Type 1) regarding steps, heart rate, and sleep, and 'aggregated data' (Type 2), visualizing heart rate and sleep quality, satisfy their information needs. Notably, around 50% of the users agree (Mdn equals 4) that the tracked sleep diagrams (Type 2) help to identify and to interpret differences and saliences. Furthermore, Table 3.2 revealed that raw data regarding heart rate and sleep is more preferred than aggregated data. While 401 participants are viewing and using the heart rate as raw data (Type 1) to gain awareness, fewer participants are looking at the diagrams (N=288) and using them (N=287), even if they are mainly satisfied (Mdn equals 4).

Table 3.2: Satisfied information needs and information use regarding steps, heart rate, and sleep; Type 1, raw data; Type 2, aggregated data; Mdn, median; IQR, interquartile range.

Need to positive behaviour change				
Feature	**Awareness**	**Improvement**	**Assessment**	**Identification/ Interpretation**
Steps (Type 1)				
Information need	n=576, Mdn(4), IQR(1)	n=575, Mdn(5), IQR(1)	n=575, Mdn(5), IQR(1)	-
Information use	n=575, Mdn(4), IQR(1)	n=575, Mdn(4), IQR(1)	n=575, Mdn(4), IQR(1)	-
Steps (Type 2)				
Information need	n=408, Mdn(4), IQR(1)	n=409, Mdn(4), IQR(1)	n=408, Mdn(4), IQR(1)	n=409, Mdn(4), IQR(1)
Information use	n=407, Mdn(4), IQR(1)	n=406, Mdn(4), IQR(1)	n=407, Mdn(4), IQR(1)	n=407, Mdn(4), IQR(1)

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Need to positive behaviour change				
Feature	**Awareness**	**Improvement**	**Assessment**	**Identification/ Interpretation**
Heart rate (Type 1)				
Information need	n=401, Mdn(5), IQR(1)	n=400, Mdn(4), IQR(2)	n=401, Mdn(4), IQR(1)	-
Information use	n=401, Mdn(4), IQR(1)	n=400, Mdn(4), IQR(2)	n=401, Mdn(4), IQR(1)	-
Heart rate (Type 2)				
Information need	n=288, Mdn(4), IQR(1)	n=287, Mdn(4), IQR(2)	n=288, Mdn(4), IQR(1)	n=288, Mdn(4), IQR(1)
Information use	n=287, Mdn(4), IQR(1)	n=287, Mdn(4), IQR(2)	n=286, Mdn(4), IQR(1)	n=286, Mdn(4), IQR(1)
Sleep (Type 1)				
Information need	n=472, Mdn(4), IQR(1)	n=472, Mdn(4), IQR(2)	n=472, Mdn(4), IQR(1)	-
Information use	n=472, Mdn(4), IQR(1)	n=472, Mdn(4), IQR(1)	n=471, Mdn(4), IQR(1)	-
Sleep (Type 2)				
Information need	n=380, Mdn(4), IQR(1)	n=379, Mdn(4), IQR(2)	n=379, Mdn(4), IQR(1)	n=379, Mdn(4), IQR(1)
Information use	n=379, Mdn(4), IQR(1)	n=378, Mdn(4), IQR(1.25)	n=378, Mdn(4), IQR(1)	n=379, Mdn(4), IQR(1)

3.5.2 RQ2: How Do Fitbit Users Perceive the Readability of Explanations about Heart Rate Zones and Sleep Stages' Characteristics (Type 3)?

Table 3.3 shows the perceived readability of Fitbit's heart rate zones explanation. The heart rate zones explanation includes information such as "Cardio (70-84% max heart rate) is the medium to high intensity exercise zone. In this zone, you are pushing yourself but not straining. For most people, this is the exercise zone to target"; or, "Zones are calculated based on a max heart rate of 220 bpm minus your age." The investigation differentiates between users who already knew the explanations and users who saw them for the first time. More than half of the participants who are consciously using the heart rate function did notice the listed explanation. Users who already knew the explanations as well as users who saw them for the first time mostly tend to agree (Mdn equals 4) that the readability is given (easy to understand, interesting, and not too long).

A Mann-Whitney U test was performed to determine if there were differences in the distributions of the answers (MRs) regarding the perceived readability. The distribution of the answer to the question whether the explanation about heart rate zones is easy to understand differs significantly (U=13410.000, z=-2.824, p$\leq 0.01^{**}$). According to Table 3.3, the MR for users who already knew the explanations is higher (MR=206.61) than for the users who saw the heart rate zones explanations for the first time and perceived them as easy to understand (MR=176.23). This leads to the conclusion that participants who already knew the heart rate zones explanation have higher ranks (generally tend to agree stronger) than for users who saw them for the first time.

Table 3.3: Measured agreement or disagreement on readability regarding heart rate zones explanation; Type 3, explanations; MR, mean rank; Mdn, median; IQR, interquartile range.

Readability	**Users, who knew it (N=286)**	**Users, who saw it for the first time (N=116)**
Heart rate zones (Type 3)		
I perceive the explanations easy to understand.	n=283 MR(206.61) Mdn(4), IQR(1)	n=112 MR(176.23) Mdn(4), IQR(0)
I perceive the explanations interesting.	n=283 MR(204.54) Mdn(4), IQR(1)	n=113 MR(183.38) Mdn(4), IQR(0)
I perceive the explanations not too long.	n=283 MR(202.39) Mdn(4), IQR(1)	n=110 MR (183.15) Mdn(4), IQR(0.25)

Table 3.4 shows the perceived readability of Fitbit's sleep stages' characteristics. The sleep stages' characteristics explain, for example, "At night, your body cycles through different Sleep Stages. It usually moves from light sleep to deep sleep, back to light, then into REM, though sleep cycles vary naturally"; or, "You were [...] in Deep sleep. Deep sleep helps with physical recovery and aspects of memory and learning. If you're feeling extra refreshed, you likely spent some solid time in this stage." Table 3.4 attracts attention as the number of participants who knew it is much higher (N=420) than in comparison to the heart rate zones explanation (Table 3.3). In contrast, the number of users who saw the sleep stages' characteristics for the first time is smaller. Here, participants of both samples mainly agree (Mdn equals 4) that the readability of the sleep stages' characteristics is present. Nevertheless, the applied U test revealed that the distributions of the answers, whether the information is easy to understand, interesting, and not too long differ significantly. Users who already knew the explanation tend to agree more (MR = 235.07) than users who saw it for the first time (MR=163.91) that it is easy to understand (U = 5612.500, z = - 3.618, p$\leq$0.001***). These findings behave similarly

for finding the explanation interesting (U=5891.000, z = -3.192, $p \leq 0.01^{**}$) and not too long (U = 5733.500, z = -3.130, $p \leq 0.01^{**}$). In both cases, the MR of users who knew it is higher than for users who saw the sleep stages explanation for the first time.

Table 3.4: Measured agreement or disagreement on readability regarding sleep stages' characteristics explanation. Type 3, explanations; MR, mean rank; Mdn, median; IQR, interquartile range.

Readability	**Users, who knew it (N= 420)**	**Users, who saw it for the first time (N=39)**
Sleep stages' characteristics (Type 3)		
I perceive the explanations easy to understand.	n = 418 MR(235.07) Mdn(4), IQR(1)	n=39 MR(163.91) Mdn(4), IQR(0)
I perceive the explanations interesting.	n = 418 MR(234.41) Mdn(4), IQR(1)	n=39 MR(171.05) Mdn(4), IQR(1)
I perceive the explanations not too long.	n = 417 MR(233.25) Mdn(4), IQR(1)	n=38 MR(170.38) Mdn(4), IQR(0)

3.5.3 RQ3: To What Extent Do Users Understand the Provided Explanations (Type 3) and How Do They Estimate Their Usefulness?

Table 3.5 shows that participants, both those who already knew the heart rate zones explanation and users who saw them for the first time, are tending mainly to agree on the usefulness and understandability of the provided information. Both user groups mostly agree (Mdn equals 4) that the explanation is necessary and trustworthy. Furthermore, they also mostly agree that the explanation is sufficient and that they do not have further questions (Mdn equals 4), and that the explanation is not overloaded with information (Mdn equals 4). This observation is also applicable regarding understanding the explanations. Both user groups mainly agree that they learned new things (Mdn equals 4), know how to use the obtained information (Mdn equals 4), and understand how Fitbit is calculating the data (Mdn equals 4).

Furthermore, both groups of users who knew it or got to know it during the survey mainly disagree (Mdn equals 2) that the technical terms and sentences are difficult to understand. According to the aspect of using the information to make good health decisions, users who knew it also mostly agree (Mdn equals 4) that they reflected on their behavior based on this explanation. Users tend to answer mainly neutral regarding the statement that they adapted their behavior (Mdn equals 3). The users who saw the explanation for the first time also mainly agree that they will both reflect on (Mdn equals 4) and adapt (Mdn equals 3, mode equals 4) their behavior based on the explanation in the future. Here, only the distributions of answers regarding the assessment are significantly different. The MR for users who knew the heart rate zones explanation is higher (MR=205.30) than for users who saw it for the first time (MR=175.91) regarding the statement that the information is not overloaded with information (U=13310.000, z=-2.697, p$\leq 0.01^{**}$). Further, the distributions of the answers between the two groups also differ significantly regarding the statement that the explanation is necessary (U=13274.000, z=-3.144, p$\leq$0.01**).

The MR for users who already knew the heart rate zones explanation (MR=209.76) is higher than for users who saw them for the first time (MR=173.94).

Table 3.5: Perceived usefulness and understandability of heart rate zones explanation. Type 3, explanations; MR, mean rank; Mdn, median; IQR, interquartile range.

Usefulness and understandability of provided information	**Users, who knew it (N=286)**	**Users, who saw it for the first time (N=116)**
Heart rate zones (Type 3)		
I perceive the explanations necessary.	n = 284 MR(209.76) Mdn(4), IQR(1)	n = 114 MR(173.94) Mdn(4), IQR(0)
I perceive the explanations not overload with information.	n = 282 MR(205.30) Mdn(4), IQR(0)	n = 111 MR(175.91) Mdn(4), IQR(0)
I perceive the explanations trustworthy.	n = 280 MR(201.15) Mdn(4), IQR(1)	n = 109 MR(179.19) Mdn(4), IQR(1)
Based on the explanation the technical terms and sentences are difficult to understand.	n = 284 MR(195.15) Mdn(2), IQR(1)	n = 112 MR(207.00) Mdn(2), IQR(1)
Based on the explanation I learned new things.	n = 283 MR(203.71) Mdn(4), IQR(1)	n = 114 MR(187.31) Mdn(4), IQR(2)
Based on the explanation I know how to use the obtained information.	n = 284 MR(201.73) Mdn(4), IQR(0.75)	n = 111 MR(188.45) Mdn(4), IQR(1)
Based on the explanation I can understand how Fitbit is calculating my heart rate data (e.g., during a day, while exercising).	n = 284 MR(200.26) Mdn(4), IQR(0)	n = 112 MR(194.04) Mdn(4), IQR(0)
Based on the explanation I perceive the information as sufficient and do not have any further questions on this topic.	n = 282 MR(199.09) Mdn(4), IQR(1)	n = 113 MR(195.27) Mdn(4), IQR(1)

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Usefulness and understandability of provided information	**Users, who knew it (N=286)**	**Users, who saw it for the first time (N=116)**
Heart rate zones (Type 3)		
Based on the explanation I will reflect my heart rate data (e.g., during a day, while exercising).		n = 113 MR(185.96) Mdn(4), IQR(1)
Based on the explanation I reflected my heart rate data (e.g., during a day, while exercising).	n = 281 MR(202.14) Mdn(4), IQR(1)	
Based on the explanation I will adapt my exercises.		n = 113 MR(213.48) Mdn(3), IQR(1)
Based on the explanation I adapted my exercises.	n = 282 MR(191.80) Mdn(3), IQR(2)	

Contrary to the heart rate zones explanation in Table 3.5, Table 3.6 shows two cases where the Mdn is different. Users who saw the leep stages' characteristics for the first time tend to be mostly neutral (Mdn equals 3) as opposed to users who already knew it and tended to mostly agree that the explanation is trustworthy (Mdn equals 4). This is similar regarding the understanding how Fitbit is calculating the data.

Regarding the sleep stages' characteristics explanations, the MR and, therefore, the distributions of the answers for both types of users differ significantly regarding some aspects. Distributions of the participants' agreement on the statements such as "I learned new things" ($U=6642.500$, $z=-2.051$, $p \leq 0.05^{*}$), not overloaded with information ($U=6116.000$, $z= -2.599$, $p \leq 0.01^{**}$), sufficient ($U=6283.000$, $z=-2.449$, $p \leq 0.05^{*}$), understanding how the data is calculated ($U=5002.000$, $z= -4.318$, $p \leq 0.001^{***}$), trustworthiness ($U=5673.500$, $z=-3.299$, $p \leq 0.001^{***}$), and necessity ($U=5813.500$, $z=-2.970$, $p \leq 0.01^{**}$) significantly differ between both groups. Regarding all these statements, the MR for users who already knew the sleep stage explanation is higher than for the other group, which revealed that they tend to agree stronger.

Table 3.6: Perceived usefulness and understandability sleep stage characteristics' explanations; Type 3, explanations; MR, mean rank; Mdn, median; IQR, interquartile range.

Usefulness and understandability of provided information	**Users, who knew it (N=420)**	**Users, who saw it for the first time (N=39)**
Sleep stages' characteristics (Type 3)		
I perceive the explanations necessary.	n = 418 MR(233.59) Mdn(4), IQR(0.25)	n = 38 MR(172.49) Mdn(4), IQR(1)
I perceive the explanations not overload with information.	n = 415 MR(231.26) Mdn(4), IQR(1)	n = 38 MR(180.45) Mdn(4), IQR(0)
I perceive the explanations trustworthy.	n = 412 MR(231.73) Mdn(4), IQR(0)	n = 39 MR(165.47) Mdn(3), IQR(1)
Based on the explanations the technical terms and sentences are difficult to understand.	n = 416 MR(227.04) Mdn(2), IQR(1)	n = 39 MR(238.19) Mdn(2), IQR(1)
Based on the explanations I learned new things.	n = 417 MR(232.07) Mdn(4), IQR(1)	n = 39 MR(190.32) Mdn(4), IQR(1)
Based on the explanations I know how to use the obtained information.	n =416 MR(230.81) Mdn(4), IQR(1)	n = 39 MR(198.00) Mdn(4), IQR(1)
Based on the explanations I can understand how Fitbit is illustrating/calculating my tracked sleep.	n = 416 MR(235.48) Mdn(4), IQR(0)	n = 39 MR(148.26) Mdn(3), IQR(2)
Based on the explanations I perceive the information as sufficient and do not have any further questions on this topic.	n = 414 MR(231.32) Mdn(4), IQR(1)	n = 39 MR(181.10) Mdn(4), IQR(2)
Based on the explanations I will reflect my tracked sleep.		n = 39 MR(158.29) Mdn(4), IQR(1)
Based on the explanations I reflected my tracked sleep.	n = 415 MR(234.00) Mdn(4), IQR(0)	

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Usefulness and understandability of provided information	**Users, who knew it (N=420)**	**Users, who saw it for the first time (N=39)**
Sleep stages' characteristics (Type 3)		
Based on the explanations I will adapt my sleep behavior.		n = 39 MR(199.14) Mdn(3), IQR(1)
Based on the explanations I adapted my sleep behavior.	n = 415 MR(230.17) Mdn(3), IQR(2)	

3.6 Discussion

3.6.1 Fitbit Users' Needs and Satisfaction Based on Using the Provided Information (Type 1 and Type 2) (RQ1)

The participants of this study mainly agree that they are using the three surveyed features (steps, heart rate, and sleep quality) of Fitbit. According to Feng and Agosto (2017), who reported that 74% of their participants use their tracker almost all the time, the sample in this study shows similar characteristics.

Most participants agree that they need to become more aware, improve their health and fitness-related behavior, and assess their behavior. Therefore, they agreed that they need the information provided by Fitbit. This investigation shows that the users in this study use the information provided by their activity trackers to meet their information need, and consequently, their health and fitness-related needs. These findings can be associated with Feng and Agosto (2017, 2019a) as they also found that users apply provided raw data and aggregated data displayed as diagrams. Furthermore, as the participants mostly agree that using the information enables them to satisfy their needs, this could indicate that results are easy to use and clearly presented. This is in line with Feng et al. (2017), who reported that their participants mainly agreed that information (e.g., raw data, diagrams) by activity tracking technologies are clearly presented.

Nevertheless, users within this sample tend to use diagrams a little less than raw data. The participants agree that they are using the diagrams to interpret and identify differences and saliences in their tracked data. As Gouveia et al. (2015) found out that their participants were in a short engagement phase, we assume that our participants also tend to have a quick look at the raw data instead of intensive reviewing and engaging with information by using diagrams (which include more detailed information). Furthermore, interpreting and identifying differences/saliences might also be useful if one considers greater amount of data over an extended period to compare those data with each other. This could be connected to the findings of Gouveia et al. (2015) that users were not interested in reflecting on data tracked in the past and, therefore, did not prefer the diagrams to the raw data. Reflecting on data tracked and interpreting or identifying these data are much more complex activities and need more time than gaining awareness regarding the current amount of steps or heart rate. The results also confirmed that the reason to buy an activity tracker does not need to be the same for everyone. As Rooksby et al. (2014) already mentioned, users have different goals such as documentation (e.g., awareness, reflection, confirmation) and diagnostic tracking (e.g., identification of connections between things, searching for an answer for situations). Participants in this study seem to tend to use it rather for documentary needs.

According to Hirvonen et al. (2012), we conclude that participants' information needs and use in this study do not mainly require diagrams and that raw data seems already sufficient. The results confirm our assumption that diagrams are needed regarding higher task complexities and levels of activities such as interpreting and identifying differences and saliences as they provide detailed information instead of raw data. But they are also used for gaining awareness, improvement, and assessment of their own health and fitness-related behavior as well.

Even if most participants agree on interpreting differences and saliences, some participants disagree that the provided tracked sleep data is useful. This confirms the results by Maher et al. (2017) where a few participants did not know how to interpret or use the data. These results are also in line with Zhang et al. (2019), who call attention to the fact that wearables do not give suggestions. Therefore, users with higher task complexities are on their own. Diagrams could be interesting, but they might not be useful without knowing how to apply them. Users can try to interpret and to connect their insights with their environment and their behavior, but these insights are solely based on their own interpretation and knowledge. Therefore, it is also crucial to support users who want to gain added value from the diagrams and elaborate on their possibilities to improve health and fitness- related behavior. Especially if users might not have a solid knowledge about the heart rate zones, it is advisable to integrate the explanations into the diagrams as well. According to Patel and O'Kane (2015), users want to monitor their progress to measure and improve their exercising behavior. The users in this study mainly agree that they are also looking at their heart rate to improve it by making use of the diagrams.

3.6.2 Perceived Readability of Heart Rate Zones and Sleep Stages' Characteristics (RQ2)

According to Nelson et al. (2016), the engagement with wearables and herewith provided information depends also on the readability. The participants' evaluation is mainly positive as they agree that the information is not too long, easy to understand, and interesting. This is crucial, as the use of information can be affected negatively by the length. According to Case and Given (2016), information overload can lead to information avoidance. Therefore, activity tracking technologies must provide useful and user-friendly information to support and enhance the use of information. Furthermore, curiosity plays an important role as well, especially if the information has serendipity like in this survey. The survey's design showed that users who saw the explanations for the first time consumed the information passively, as provided by the authors. Provided information needs to be interesting and at least useful; otherwise, the motivation to read information might be undermined.

3.6.3 Activity Tracking Technologies and Perceived Usefulness and Understandability of Provided Information (RQ3)

Regarding the health information behavior of the participants, there are further parallels to the study of Feng and Agosto (2019a). Users fulfill meta-level activities by using and thinking about the collected personal information, and by reflecting on those tracked data and evaluating it.

Concluding based on the results, both user groups mainly perceived the provided information as useful and easy to understand. They assess and make use of the explanations towards healthier behavior. Based on the explanations, they mostly agree that they already reflected on their behavior or adapted their behavior or would like to do this in the future. The explanations support users to better understand which heart rate zones they are exercising or to identify where optimization regarding sleep cycles is needed. Interestingly, explanations of the heart rate zones are highlighted in the application's settings. The explanation is not directly linked to the charts and diagrams. Therefore, users need to know where the explanation is placed and that it exists. The sleep stages' characteristics explanations are integrated directly within the diagrams. Fitbit users do not need to search for it in the settings. We assume that this might also be one reason why many participants in comparison to sleep stages did not recognize the heart rate explanations and saw it for the first time during the survey.

Furthermore, most participants also agree that the information is necessary. The explanation of the heart rate zones enables insight regarding the meaning of each zone. Therefore, users have the chance to use these insights and to better decide if their training was satisfying. To understand if an exercise was successful, they must know if they would like to exercise in the cardio or fat-burning zone. Even if users mostly agree that they understand the explanations and know how to use the information—we would suggest involving experts (e.g., fitness coaches, doctors) to better identify differences and knowing how to use such insights.

The sleep stages explanation includes the sleep stages' characteristics. But this does not help to fix the sleep behavior or to change it. Users must know how to change a specific behavior. First insights are a solid start (to gain awareness, to improve bedtimes and duration, to evaluate if there was enough sleep), but more is needed than an indication that the sleep quality is 'bad' or 'good.' Furthermore, we assume that changing behavior regarding the sleep stage explanation might be more complicated than to reflect on it. Here, users tend to be neutral about the statement that they adapted their behavior based on the sleep stage explanation. On the contrary, they mostly tend to agree that they reflected their behavior based on the explanation. This might also be an indicator that the complexity of reflecting on the behavior and adapting the behavior differs. One can reflect on data and think about it, but one still does not need to come to a conclusion on how to improve or change a behavior based on tracked data. Users need to understand the characteristics of the sleep stages and how they can change them. Therefore, this investigation confirmed equally like McKinney, Cox, and Sbaffi (2019) that tracking is an intensive activity.

3.7 Limitations and Conclusion

The investigation concentrated on Fitbit users as a single case. It would be helpful to conduct further similar studies with users of other activity tracking technologies such as Garmin, Samsung Gear, or Apple Watch. This would enable a comparison regarding the presentation of explanations and their usefulness. Furthermore, most participants are exercising 1-2 or three or more times per week. This and the fact that half of the participants are long-term users might bias the results. Further studies need to concentrate on newbies and also on users who are exercising less. Furthermore, a limitation of this study is predefined answers. This allows only a limited insight regarding the information behavior of activity tracking technologies. Here we suggest that interviews would expand the understanding of information behavior in the context of activity tracking technologies in the future. Furthermore, we did not measure the level of health information literacy; rather, we asked for participants' estimation if they are able to assess, use, and reflect on the data. Future investigations are needed to measure to what extent users of activity tracking technologies are health information literate. This could include investigations on aspects such as if they are seeking further information to better understand the explanations and, if so, how they seek further information, how they evaluate different obtained information and sources, and how they are synthesizing this information in detail.

This investigation ties in with previous studies and underlines the diversity and complexity of activity tracking technology studies. It is difficult to achieve a balance and to satisfy all kinds of users. As Case and Given (2016) mentioned, information overload can lead to stopping use of the information and, consequently, the device. In this study, the users mainly agree that the explanations were not too long. The question arises if users need maybe more detailed information regarding adapting the behavior. But results by Kinney, Nabors, Merianos, and Vidourek (2019) showed that there was no significant evidence towards a relation showing that the more information users are applying, the more they feel confident to be physically active. Nevertheless, our investigation shows that using two types of information (Type 1: raw data and Type 2: diagrams) provided by Fitbit satisfied the users' information needs. Especially the explanations (Type 3) are characterized as necessary and easy to understand by most users. More to the point, users mainly agree that they know how to use obtained information by looking at explanations.

The improvement of one's health and fitness-related behavior requires more than only acquiring information or gained knowledge. Activity tracking technologies might be motivators but not facilitators. First, users need the willingness to change or to recognize the need to improve health and fitness-related behavior. Second, users need the knowledge or ability to adapt knowledge to improve their behavior individually. The latter skill is not directly provided by visualizations of the collected data, as they do not contain suggestions on how to use specific observations. Fitbit already offers notifications regarding sleep quality, but these are general advocacies. Even if most participants agree that the tracked sleep data improves their sleep quality, there are also cases where users disagree. Regarding the diagrams, users get possibilities to compare themselves with average values. At this point, we stress that the solution is not to solely offer more information, but that it also needs to be useful and necessary. Users who are interested in improving their health and fitness-related behavior should get support through gyms and health insurance, as well as through educators in school or university.

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Supplemental Materials

The survey was uploaded on Zenodo and is accessible via this link (DOI): 10.5281/zenodo.4001741 (see Appendix)

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3.8 Appendix

Table 3.7: Survey Insights

Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
1*	Exclusion criterion	Before we start, the crucial question first: Do you use a Fitbit activity tracker? **Important**: *The sole mobile tracking with the Fitbit application is here not counted as a Fitbit activity tracker. It has to be a Fitbit device (wearable).*	Yes-no question • yes [#2] • no [Finish survey]
2*	Exercise (frequency)	How often do you exercise (e.g., going to the gym, workouts at home, workouts outside, other sports, etc.)?	I'm exercising • never • few times per year • every few months • once a month • several times per month • 1-2 times per week • 3 or more times per week • every day • I prefer not to say.
3*	Fitbit (usage frequency)	Since when have you been using your Fitbit activity tracker?	Since: • less than a week • 1-2 weeks • 3 weeks • a month • several months • a year • several years

Continued on next page

Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
4		Did you use any other activity trackers before your Fitbit activity tracker? If so, I would be happy to receive more information, such as which device, how long you have been using it or are using it, etc. *Otherwise, you can skip this page by clicking* **Next**.	[Free text field]
5*	Fitbit (wearing frequency)	How frequently do you wear your Fitbit activity tracker?	Single selection • Only while exercising • Only while sleeping • Only when I'm leaving the house • Throughout the whole day but not while sleeping • Throughout the whole day and night (including sleeping) • Irregularly • Other usage frequencies: [Free text field]
Steps			
6*	Exclusion criterion	Are you consciously using the tracking of your steps with your Fitbit activity tracker? **Consciously** means here that you are deliberately looking at your Fitbit activity tracker/application.	Yes-no question • yes [#6.1] • no [#7]
Please note that the following page is about **your expectation** *regarding the tracking of the steps. This means I want to know* **why** *you are using the function.*			

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
6.1*	Steps (wrist-band/ appli-cation) expec-tation	Please evaluate if the following statements apply to you: I'm looking at the count of my steps on my Fitbit tracker/application because I want to . . .	Rating scale (1-5)
6.1.1*		develop an awareness for my physical activity. (e.g., counted steps after work, how many steps do I walk from my front door due to the main station, etc.)	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
6.1.2*		improve my physical activity. (e.g., to take the stairs more often, to walk more often, etc.)	
6.1.3*		to assess my physical activity. (e.g., did I walk a lot of steps, did I walk too few steps, etc.)	
Please note that the next page is **no longer about your expectation (!)** *but about* **your experience**. *This means that I would like to know* **to what extent the function makes certain changes possible**.			
6.2*	Steps (wrist-band/ appli-cation) experi-ence	Please evaluate if the following statements apply to you: Looking at my counted steps on my Fitbit tracker/application enables me to ...	Rating scale (1-5)
6.2.1*		develop an awareness for my physical activity.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
6.2.2*		improve my physical activity.	
6.2.3*		assess my physical activity.	
6.3*	Exclusion criterion	Are you using the visual illustrations (diagrams) within the Fitbit application related to your counted steps?	Yes-no question • yes [#6.4] • no [#7]
Please note that the following page is about your **expectation** *regarding the*			
Continued on next page			

Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
visual illustrations (diagrams). This means I want to know **why** *you are using the visual illustrations (diagrams).*			
6.4*	Steps visual illustrations (diagrams) expectation	Please evaluate if the following statements apply to you: I'm looking at the visual illustrations (diagrams) within the Fitbit application related to my counted steps because I want to ...	Rating scale (1-5)
6.4.1*		develop an awareness for my physical activity.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
6.4.2*		improve my physical activity.	
6.4.3*		assess my physical activity.	
6.4.4*		identify and interpret differences/saliences.	
Please note that the next page is **no longer about your expectation (!)** *but about* **your experience**. *This means that I would like to know to what extent* **the visual illustrations (diagrams) make certain changes possible**.			
6.5*	Steps visual illustrations (diagrams) experience	Please evaluate if the following statements apply to you: Looking at the visual illustrations (diagrams) of my counted steps within the Fitbit application enables me to ...	Rating scale (1-5)
6.5.1*		develop an awareness for my physical activity.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
6.5.2*		improve my physical activity.	
6.5.3*		assess my physical activity.	
6.5.4*		identify and interpret differences/saliences.	

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
7*	Exclusion criterion	Does your Fitbit activity tracker offer the possibility to track your heart rate?	Yes-no question • yes [#8] • no [#9]
8*	Exclusion criterion	Are you consciously using the tracking of your heart rate with your Fitbit activity tracker? Consciously means here that you are deliberately looking at your Fitbit activity tracker/application.	Yes-no question • yes [#8.1] • no [#9]
Please note that the following page is about **your expectation** *regarding the tracking of the heart rate. This means I want to know* **why** *you are using the function.*			
8.1*	Heart rate (wristband/ application) expectation	Please evaluate if the following statements apply to you: I'm looking at my heart rate on my Fitbit tracker/application because I want to . . . *Important: Here, diagrams are not intended.*	Rating scale (1-5)
8.1.1*		develop an awareness for my heart rate (e.g., during a day, while exercising). *(e.g., how low/high is my heart rate during a walk, during sitting, during shopping, at work, during sports, etc.)*	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.1.2*		improve my heart rate (e.g., during a day, while exercising). *(e.g., reduce my heart rate if it is too high while exercising; increase my heart rate if it is too low while exercising; I would like to reduce my all-day heart rate, etc.)*	

Continued on next page

Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
8.1.3*		assess my heart rate (e.g., during a day, while exercising). *(e.g., to assess if my heart rate is too low or too high during a walk, while sitting, during sports.)*	
Please note that the next page is **no longer about your expectation (!)** *but about* **your experience**. *This means that I would like to know* **to what extent the function makes certain changes possible.**			
8.2*	Heart rate (wrist-band/ appli-cation) experi-ence	Please evaluate if the following statements apply to you: Looking at my heart rate on my Fitbit tracker/application enables me to ... *Important: Here, diagrams are not intended.*	Rating scale (1-5)
8.2.1*		develop an awareness for my heart rate (e.g., during a day, while exercising).	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.2.2*		improve my heart rate (e.g., during a day, while exercising).	
8.2.3*		assess my heart rate (e.g., during a day, while exercising).	
8.3*	Heart rate visual illustra-tions (dia-grams)	Are you using the visual illustrations (diagrams) of the Fitbit application related to your tracked heart rate (e.g., resting heart rate, 30 days average, evaluation of workouts)?	Yes-no question • yes [#8.4] • no [#8.6]
Please note that the following page is about **your expectation** *regarding the visual illustrations (diagrams). This means I want to know* **why** *you are using the visual illustrations (diagrams).*			
Continued on next page			

Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
8.4*	Heart rate visual illustrations (diagrams) expectation	Please evaluate if the following statements apply to you: I'm looking at the visual illustrations (diagrams) within the Fitbit application related to my tracked heart rate because I want to ...	Rating scale (1-5)
8.4.1*		develop an awareness for my heart rate (e.g., during a day, while exercising).	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.4.2*		improve my heart rate (e.g., during a day, while exercising).	
8.4.3*		assess my heart rate (e.g., during a day, while exercising).	
8.4.4*		identify and interpret differences/saliences.	
Please note that the next page is **no longer about your expectation (!)** *but about* **your experience**. *This means that I would like to know* **to what extent the visual illustrations (diagrams) make certain changes possible.**			
8.5*	Heart rate visual illustrations (diagrams) experience	Please evaluate if the following statements apply to you: Looking at the visual illustrations (diagrams) of my tracked heart rate within the Fitbit application enables me to ...	Rating scale (1-5)
8.5.1*		develop an awareness for my heart rate (e.g., during a day, while exercising).	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.5.2*		improve my heart rate (e.g., during a day, while exercising).	
8.5.3*		assess my heart rate (e.g., during a day, while exercising).	
8.5.4*		identify and interpret differences/saliences.	

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Table 3.7 – continued from previous page

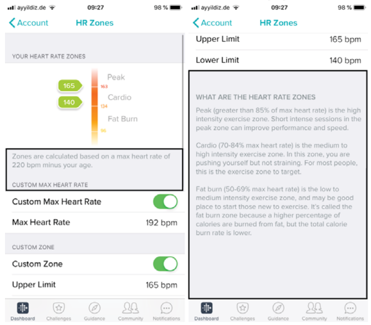
#	Subject	Question	Answer Typ
8.6*	Heart rate zones explanation (Type 3)	Did you notice the explanation listed below within the Fitbit application? 	Yes-no question • yes [#8.7 - #8.8] • no [#8.9 - #8.10]
Users, who already knew the explanations			
The already showed explanations will be shown again to answer questions related to those explanations. Please read them carefully and consciously.			
8.7*		Please evaluate if the following statements apply to you: I perceive the explanations "What Are The Heart Rate Zones" ...	Rating scale (1-5)
8.7.1*		easy to understand.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.7.2*		interesting.	
8.7.3*		not too long.	
8.7.4*		trustworthy.	
8.7.5*		not overload with information.	
8.7.6*		necessary.	
8.7.7	Further Comments	If you would like to explain your decision if the explanation is/is not necessary, I would be very thankful. *Otherwise, you can skip this input field.*	[Free text field]
The already shown explanations will be displayed for the last time to answer the last questions related to those explanations.			

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
8.8*		Please evaluate if the following statements apply to you: Based on the explanation "What Are The Heart Rate Zones" ...	Rating scale (1-5)
8.8.1*		I learned new things.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.8.2*		the technical terms and sentences are difficult to understand.	
8.8.3*		I know how to use the obtained information.	
8.8.4*		I can understand how Fitbit is calculating my heart rate data (e.g., during a day, while exercising).	
8.8.5*		I perceive the information as sufficient and do not have any further questions on this topic.	
8.8.6*		I reflected my heart rate data (e.g., during a day, while exercising) based on the explanation. *(e.g., the explanation helped me to better understand my heart rate and/or in which heart rate zones I'm exercising, etc.)*	
8.8.7*		I adapted my exercises based on the explanation.	
Users, who saw the explanations for the first time			
The already showed explanations will be shown again to answer questions related to those explanations. Please read them carefully and consciously.			
8.9*		Please evaluate if the following statements apply to you: I perceive the explanations "What Are The Heart Rate Zones" ...	Rating scale (1-5)

Continued on next page

Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
8.9.1*		easy to understand.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.9.2*		interesting.	
8.9.3*		not too long.	
8.9.4*		trustworthy.	
8.9.5*		not overload with information.	
8.9.6*		necessary.	
8.9.7	Further Comments	If you would like to explain your decision if the explanation is/is not necessary, I would be very thankful. *Otherwise, you can skip this input field.*	[Free text field]
The already shown explanations will be displayed for the last time to answer the last questions related to those explanations.			
8.10*		Please evaluate if the following statements apply to you: Based on the explanation "What Are The Heart Rate Zones" ...	Rating scale (1-5)
8.10.1*		I learned new things.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
8.10.2*		the technical terms and sentences are difficult to understand.	
8.10.3*		I know how to use the obtained information.	
8.10.4*		I can understand how Fitbit is calculating my heart rate data (e.g., during a day, while exercising).	
8.10.5*		I perceive the information as sufficient and do not have any further questions on this topic.	

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
8.10.6*		I will reflect my heart rate data (e.g., during a day, while exercising) based on the explanation. *(e.g., the explanation can help me to better understand my heart rate and/or in which heart rate zones I'm exercising, etc.)*	
8.10.7*		I will adapt my exercises based on the explanation.	
Sleep			
9*		Does your Fitbit activity tracker offer the possibility to track your sleep?	Yes-no question • yes [#10] • no [#11]
10*		Are you consciously using the sleep tracking with your Fitbit activity tracker? *Consciously means here that you are deliberately looking at your Fitbit activity tracker/application.*	Yes-no question • yes [#10.1] • no [#11]
Please note that the following page is about ***your expectation*** *regarding the sleep tracking.This means I want to know* ***why*** *you are using the function.*			
10.1*	Sleep tracking (wristband/application) expectation	Please evaluate if the following statements apply to you: I'm looking at my tracked sleep (e.g., sleep duration, sleep stages) on my Fitbit tracker/application because I want to ... *VERY IMPORTANT: Please consider, that the absolute sleep duration and absolute number of the different sleep stages is only visible on some Fitbit trackers (e.g., Versa). Therefore, the sleep diagrams are not intended here!*	Rating scale (1-5)

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
10.1.1*		develop an awareness for my sleep quality. (e.g., when do I go to bed, when do I wake up, do I sleep differently on days where I exercise, how long do I sleep, how long am I in which stages, etc.)	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.1.2*		improve my sleep quality. (e.g., I would like to go to bed earlier, I would like to sleep longer, I would like to change specific sleep behavior habits, etc.)	
10.1.3*		assess my sleep quality. (e.g., I would like to assess if it was a "good" sleep or a "bad" sleep.)	
Please note that the next page is no longer about **your expectation (!)** *but about* **your experience**. *This means that I would like to know* **to what extent the function makes certain changes possible.**			
10.2*	Sleep tracking (wrist-band/ application) experience	Please evaluate if the following statements apply to you: Looking at my tracked sleep (e.g., sleep duration, sleep stages) on my Fitbit tracker/application enables me to ... *VERY IMPORTANT: Please consider, that the absolute sleep duration and absolute number of the different sleep stages is only visible on some Fitbit trackers (e.g., Versa). Therefore, the sleep diagrams are not intended here!*	Rating scale (1-5)

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
10.2.1*		develop an awareness for my sleep quality.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.2.2*		improve my sleep quality.	
10.2.3*		assess my sleep quality.	
10.3*	Sleep tracking visual illustrations (diagrams)	Are you using the visual illustrations (diagrams) of the Fitbit application related to your tracked sleep (e.g., 30 days average, comparison, daily sleep records)?	Yes-no question • yes [#10.4] • no [#10.6]
Please note that the following page is about **your expectation** *regarding the visual illustrations (diagrams). This means I want to know* **why** *you are using the visual illustration (diagrams).*			
10.4*	Sleep tracking visual illustrations (diagrams) expectation	Please evaluate if the following statements apply to you: I'm looking at the visual illustrations (diagrams) within the Fitbit application related to my tracked sleep because I want to ...	Rating scale (1-5)
10.4.1*		develop an awareness for my sleep quality.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.4.2*		improve my sleep quality.	
10.4.3*		assess my sleep quality.	
10.4.4*		identify and interpret differences/saliences.	
Please note that the next page is no longer about **your expectation(!)** *but about* **your experience**. *This means that I would like to*			

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
know **to what extent the visual illustrations (diagrams) make certain changes possible.**			
10.5*	Sleep tracking visual illustrations (diagrams) experience	Please evaluate if the following statements apply to you: Looking at the visual illustrations (diagrams) within the Fitbit application related to my tracked sleep enables me to ...	Rating scale (1-5)
10.5.1*		develop an awareness for my sleep quality.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.5.2*		improve my sleep quality.	
10.5.3*		assess my sleep quality.	
10.5.4*		identify and interpret differences/saliences.	
The following items [#10.6 - #10.10] are only shown if a participant said 'yes' regarding the question if the activity tracker offers heart tracking [#7]			

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Table 3.7 – continued from previous page

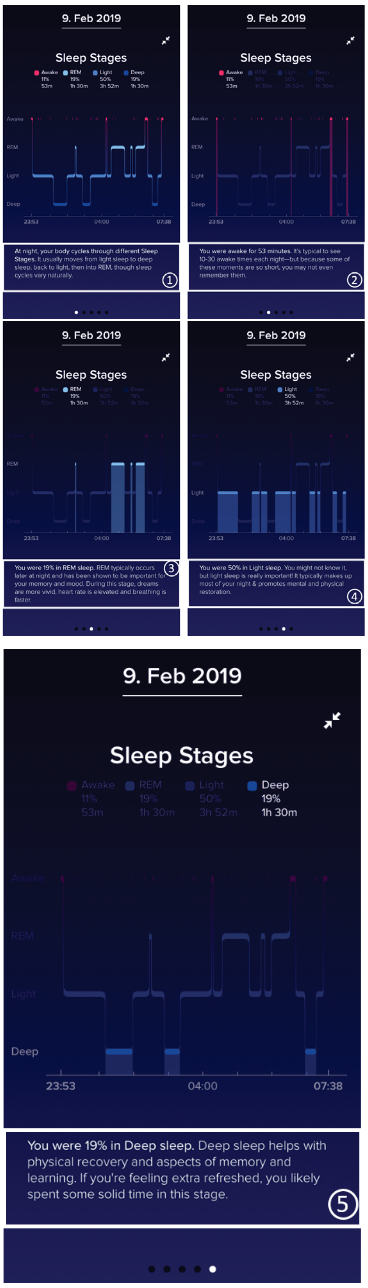
#	Subject	Question	Answer Typ
10.6*	Sleep stages' charac- teristics expla- nation (Type 3)	Did you notice the explanation listed below or similar explanations (1,2,3,4,5) within the Fitbit application? *The 1st sentence of the explanations (2,3,4,5) always corresponds to your individually recorded duration.* 	Yes-no question • yes [#10.7 - #10.8] • no [#10.9 - #10.10]
Users, who already knew the explanations			
The already showed explanations will be shown again to answer			

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
questions related to those explanations. Please read them carefully and consciously.			
10.7*		Please evaluate if the following statements apply to you: I perceive the explanations (1,2,3,4,5) above ...	Rating scale (1-5)
10.7.1*		easy to understand.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.7.2*		interesting.	
10.7.3*		not too long.	
10.7.4*		trustworthy.	
10.7.5*		not overload with information.	
10.7.6*		necessary.	
10.7.7	Further com-ments	If you would like to explain your decision if the explanation is/is not necessary, I would be very thankful. *Otherwise, you can skip this in-put field.*	[Free text field]
The already shown explanations will be displayed for the last time to answer the last questions related to those explanations.			
10.8*		Please evaluate if the following statements apply to you: Based on the explanations (1,2,3,4,5) above ...	Rating scale (1-5)
10.8.1*		I learned new things.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.8.2*		the technical terms and sen-tences are difficult to under-stand.	
10.8.3*		I know how to use the obtained information.	
10.8.4*		I can understand how Fit-bit is illustrating/calculating my tracked sleep.	
10.8.5*		I perceive the information as suf-ficient and do not have any fur-ther questions on this topic.	

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
10.8.6*		I reflected my tracked sleep based on the explanation. (e.g., the explanation helps me to better understand my tracked sleep and/or to identify where optimization is needed.)	
10.8.7*		I adapted my sleep behavior based on the explanation.	
Users, who saw the explanations for the first time			
The already showed explanations will be shown again to answer questions related to those explanations. Please read them carefully and consciously.			
10.9*		Please evaluate if the following statements apply to you: I perceive the explanations (1,2,3,4,5) above ...	Rating scale (1-5)
10.9.1*		easy to understand.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.9.2*		interesting.	
10.9.3*		not too long.	
10.9.4*		trustworthy.	
10.9.5*		not overload with information.	
10.9.6*		necessary.	
10.9.7	Further comments	If you would like to explain your decision if the explanation is/is not necessary, I would be very thankful. *Otherwise, you can skip this input field.*	[Free text field]
The already shown explanations will be displayed for the last time to answer the last questions related to those explanations.			

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
10.10*		Please evaluate if the following statements apply to you: Based on the explanations (1,2,3,4,5) above ...	Rating scale (1-5)
10.10.1*		I learned new things.	1. Strongly Disagree 2. Disagree 3. Neither Agree nor Disagree 4. Agree 5. Strongly Agree 0. I prefer not to say.
10.10.2*		the technical terms and sentences are difficult to understand.	
10.10.3*		I know how to use the obtained information.	
10.10.4*		I can understand how Fitbit is illustrating/calculating my tracked sleep.	
10.10.5*		I perceive the information as sufficient and do not have any further questions on this topic.	
10.10.6*		I will I reflect my tracked sleep based on the explanation. (e.g., the explanation can help me to better understand my tracked sleep and/or to identify where optimization is needed.)	
10.10.7*		I will adapt my sleep behavior based on the explanation.	
Background Questions			
11*	Gender	Please indicate your gender:	Single selection • female • male • I prefer not to say. • Other: [Free text field]
12*	Year of birth	Please indicate your year of birth:	Single selection [before 1920] [1920, 1921...2006] [after 2006]

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Table 3.7 – continued from previous page

#	Subject	Question	Answer Typ
13	Remarks, Suggestions & Questions	Here, you have the possibility to write down your remarks, suggestions or questions:	[Free text field]

4 Learning for a Healthier Lifestyle Through Gamification: A Case Study of Fitness Tracker Applications

Ilhan, A., & Fietkiewicz, K. J. (2019). Learning for a healthier lifestyle through gamification: A case study of fitness tracker applications. In I. Buchem, R. Klamma, & F. Wild (Eds.), *Perspectives on Wearable Enhanced Learning. Current Trends, Research and Practice*, (pp. 333-364). Springer. doi: https://doi.org/10.1007/978- 3- 319- 64301- 4_16

Abstract *Nowadays, many people have to increasingly deal with the question "How can I improve my health?" Fortunately, the market for wearable technologies (e.g., Fitbit or Garmin) supports people by enabling them to track, monitor, and analyze their physical activity. Despite the technological component, in order for the wearables to be successful, important are the user engagement design and (enhancing) users' motivation. This can be achieved with well-conceived integration of gamification elements in the fitness tracker mobile applications. A successful user engagement design of the fitness tracker applications can not only motivate the users to continually apply the service but also inspire them to be more active in the long term. There are several theories dealing with user motivation and which were considered relevant for this research: goal orientation theory, self-determination theory, and flow theory. This study concentrates on ten wearable products and their fitness tracking applications, (1) to compare the integrated gamification mechanics, (2) to analyze possible dynamics triggered by these mechanics, and (3) to identify user engagement designs supporting long-term learning and engagement in a healthier lifestyle.*

4.1 Introduction

Eight hours of sitting at the office and driving in the car to work and back home to at last lie on the sofa and enjoy the end of the day—this scenario is true for many people all over the world. Otherwise, how come "that more than 80% of the world's adolescent population is insufficiently physically active?" (World Health Organization, 2018). Tedros, World Health Organization Director-General, is right with his statement that "You don't need to be a professional athlete to choose to be active. Taking the stairs instead of the elevator makes a difference. [...] It's the choices we make each and every day that can keep us healthy. [. . .]" (World Health Organizsation, 4 June 2018). But in the end, people do not like drastic changes, and their lifestyle is usually shaped by habits. Nowadays, to actually change our lifestyle and be serious about it is perceived as a difficult challenge. Even though "insufficient physical activity is one of the leading risk factors for death worldwide" (World Health Organization, 2018), it does seem unattainable for many people to change their unhealthy habits.

Ultimately, such behavior changes like taking the stairs instead of the elevator or walking to the bakery instead of taking a car can be understood as a process of learning. "Learning is a change in human disposition or capability, which persists over a period of time, and which is not simply ascribable to processes of growth" (Gagne, 1977, p. 3). It is difficult to precisely define the time a person needs until a newly introduced behavior becomes a habit, hence, has been learned. It could last from 18, through 21 up until 254 days of repetition until an activity is automatized and can be seen as a new habit (e.g., Lally, van Jaarsveld, C. H. M., Potts, & Wardle, 2010; Rubin, October 21, 2009). With the new wearable technologies, here activity or fitness trackers, we learn to be more physically active by setting, e.g., daily step goals and orienting our behavior toward attaining a particular goal.

Ilhan and Henkel (2018) confirmed with their investigation on perceived service quality and acceptance of activity trackers that those devices have an impact on users' behavior and that they are perceived as useful. Fritz, Huang, Murphy, and Zimmermann (2014) investigated the usage of wearable technology and found out that some of their study's participants were continuously motivated by the wearables even when they were using those devices over a longer period of time. Fritz et al. (2014) made recommendations for the developers of wearables by indicating that long-term users may have other goals and motivations than new users in their first weeks of application. Therefore, it is crucial to design the activity and fitness tracker applications in an elaborate way if one wants to induce the engagement in physical activity and a healthier lifestyle in the long term.

According to IDC (2018), the demand for activity trackers is increasing. As for 2017, there were 115.4 million wearables sold all over the world. They convinced buyers with their main features such as counting steps, sleep tracking, and monitoring of heart rate. These are only few examples of their functionalities, as depending on model and price, they might offer even more features. These new Information and Communication Technologies (ICTs) make the so-called self-quantification possible. They enable people to measure, e.g., sensor-based data which is subsequently transferred into readable information. All these data can be used to manage and improve personal health. The self-quantification tools enable monitoring, collecting, and analyzing of different data, e.g., steps, burned calories, sleep duration, and more (Almalki, Gray, & Martin-Sanchez, 2016).

Activity tracker manufacturers such as Fitbit, Garmin, Samsung, or Xiaomi offer their users not only basic functionalities for self-quantification but also different game elements (mechanics) integrated in their fitness applications. These include, for example, challenges, achievements, overviews, points, and levels. To the best of our knowledge, the gamification elements implemented in activity trackers were not intensively researched until now; however, there are several studies on gamification and its motivational force to engage users in changing their behavior, for example, in educational, business, or health environment. This leads us to analyze fitness tracker applications developed by ten biggest brands, namely, Apple, Fitbit, Garmin, Huami, Moov Now, Withings, Polar, Samsung, TomTom, and Xiaomi, with focus on gamification elements (mechanics), to compare them with each other. Furthermore, we create a theoretical background for further user-oriented research in this area by linking different theories, from conceptualization and integration of gamification elements to influencing motivation and behavior change regarding physical activity with the help of fitness tracker applications.

This investigation is supposed to determine how varying user's characteristics (task- or ego-driven, intrinsically or extrinsically motivated) and their experience during exercise (flow) can affect the process of improving user's engagement and learning process to live healthier and be more physically active in the long term. First, the concept of gamification is introduced. Afterward, several theories considered relevant for research on fitness tracking apps will be presented: goal orientation theory, self-determination theory, and flow theory. Subsequently, the content of selected fitness tracking apps is analyzed, and the applied game elements are discussed in the context of aforementioned theories.

4.2 Gamification

This subchapter will introduce several definitions commonly used when describing the concept of gamification and its elements. This is necessary in order to get a general understanding of gamification components, its goals, and aspects making gamification either successful or not. There appears to be no exact definition of gamification, because the "discontent with current implementations, oversimplifications, and interpretations have led some to coin different term for their own arguable highly related practice" (Deterding, Dixon, Khaled, & Nacke, 2011, p. 9). Indeed, there are a lot of various descriptions (Deterding et al., 2011; Dicheva, Dichev, Agre, & Angelova, 2015; Huotari & Hamari, 2012; Seaborn & Fels, 2015); therefore, in the current research, it will be refrained from creating a new definition or combining the existing ones. In the course of this subchapter, the most common notions about gamification are summarized, and it will be explained which of them are suitable for this investigation.

One of the established and commonly used definitions in the research is the one by Deterding et al. (2011, p. 10): "'Gamification' is the use of game design elements in non-game context." It consists of two aspects: (1) game design elements and (2) non-game context. To understand the meaning of game design elements, it is necessary to understand the meaning of *game* itself Deterding et al. (2011). It is hardly surprising that, according to Kapp (2012), there are a lot of *game* definitions as well. One of them states: "A game is a system in which players engage in an artificial conflict, defined by rules, that results in a quantifiable outcome" (Salen & Zimmerman, 2004, p. 80).

Gamification can be understood as the implementation of game elements in a non-game environment with the objective to increase user's motivation and to trigger a specific behavior (Sailer, Hense, Mayr, & Mandl, 2017). Kapp (2012, p. 9) revealed that gamification elements and further aspects, for example, feedback, emotional reaction, or challenge, are used to support both learning and engagement. They have "the power to [. . .] inform, and educate" (Kapp, 2012, p. 10). In contrast to other authors (e.g., Huotari & Hamari, 2012; Porter, January 15th 2009; Robson, Plangger, Kietzmann, McCarthy, & Pitt, 2015), Deterding et al. (2011, p. 12) define game design elements by classifying them into five different levels: (1) game interface design patterns (badges, leaderboards, levels); (2) game design patterns and mechanics (time constraint, limited resources, turns); (3) game design principles and heuristics; (4) game models, e.g., MDA (Hunicke, LeBlanc, & Zubek, 2004); and (5) game design methods. Additionally, a definition of gamification from a service marketing perspective is laid by Huotari and Hamari (2012, p. 19): "Gamification refers to a process of enhancing a service with affordances for gameful experiences in order to support user's overall value creation." Huotari and Hamari (2012) point out that the focus of this definition is set on the goal of gamification—the gameful experiences that improve motivation and engage users in value creation. Furthermore, Huotari and Hamari (2012, p. 19) claim that "there [does not] seem to exist a clearly defined set of game elements which would be strictly unique to games, neither they automatically create gameful experiences." Seaborn and Fels (2015, p. 14) describe gamification as an "interactive system that aims to motivate and engage end-users through the use of game elements and mechanics. As yet, there is no agreed upon standard definition." Last but not least, Kapp (2012, p. 10) states that "Gamification is using game-based mechanics, aesthetics and game thinking to engage people, motivate action, promoting learning and solve problem."

There are different opinions on how these game elements should be described. Cugelman (2013, p. 2) points out that the problem with naming the game design elements is that "gamification researchers do not always agree on what these ingredients are, and some researchers take the position that these ingredients cannot even be named." Dicheva et al. (2015) show that badges are sometimes considered as game interface design (Deterding et al., 2011), game mechanic (Zichermann & Cunningham, 2011), game dynamic (Iosup & Epema, 2014), motivational affordance (Hamari, Koivisto, & Sarsa, 2014), or game component (a specific instantiation of mechanism or dynamics) (Werbach & Hunter, 2012). Zichermann and Cunningham (2011, p. 36) explain that "mechanics make up the functioning components of the game." Game design expert Amy Jo Kim explains that game mechanics "are a collection of tools and systems that an interactive designer can use to make an experience more fun and compelling" (Porter, January 15th 2009). Deterding et al. (2011, p. 12) use the term game mechanics to define such aspects as "time constraint, limited resources, turn," whereas leaderboards, badges, and levels are game interface design patterns. Kapp (2012, p. 11) points out as well that mechanics include "levels, earning badges, point system, scores, and time constraints."

As every gamification definition has its eligibility and depends on the perspective, in this investigation, all game design elements such as points, badges, time constraints, and every aspect that is developed and implemented by the game designers themselves are defined as game mechanics. In this context, *game elements* is understood as a generic term for mechanics, dynamics, and every other term related to games. However, the game mechanics (points, badges, time constraints, etc.) are not being defined as dynamics. For this study, the definition by Zichermann and Cunningham (2011, p. 36) was chosen and game dynamics are understood as "player's interactions with those mechanics." Kim (2015, p. 18) explains that mechanics "refer to the various actions, behaviors, and control mechanisms afforded to the player within a game context." Robson et al. (2015, p. 415) differentiate between mechanics and dynamics: "Contrary to mechanics that are set by the designer, the gamification dynamics are produced by how players follow the mechanics chosen by designer." Hence, mechanics are the gamified elements and the dynamics are the behaviors that are triggered while making use of those gamified elements (Robson et al., 2015). Furthermore, Blohm and Leimeister (2013) show which game mechanics trigger which game dynamics. For one example, rankings create a game dynamic of competition. What could be a motive to implement those game mechanics? According to Blohm and Leimeister (2013), the answer is social recognition.

One of the benefits of using game design elements is the possibility to positively motivate users (Deterding et al., 2011). Furthermore, game design elements are affecting the emotional experiences of users (Lee & Hammer, 2011). Based on this notion, gamification seems very promising regarding motivating users, but one should keep in mind that "Gamification can only provide tools [...]" and "is not a universal panacea" (Lee & Hammer, 2011, p. 148). A tool itself is not enough, so how are researchers and developers supposed to activate users' motivation and interest and be successful in a long term? Kapp (2014, p. 52) mentioned that points, badges, and leaderboards are not the success formula of a game, because "[p]eople don't play a game just for points, they play for mastery, to overcome challenges and to socialize with others." Hamari et al. (2014) clarify which motivational elements are being implemented, which psychological outcomes are caused by those elements, and which kind of behavior change is recognizable. Their analysis of 24 peer-reviewed papers revealed the positive effect of motivation affordances (e.g., badges, leaderboards, and points) (Hamari et al., 2014). One of the most popular contexts of those studies is the education/learning environment. Hamari et al. (2014) explain that in this environment, the motivation, engagement, and enjoyment related to learning new tasks have increased.

Aparicio, Vela, Sánchez, and Montes (2012) recognized that game mechanics have the potential to satisfy psychological and socially motivated needs, such as autonomy, competence, and relatedness (intrinsic motivation). Aparicio et al. (2012) recommend to select game mechanics which match with these three motivational needs. For autonomy they propose "profiles, avatars, [...], privacy control, notification control," for competence "positive feedback, optimal challenge, progressive information, [. . .], points, levels, leaderboards," and for relation "groups, messages, connection to social networks, chat" (Aparicio et al., 2012, p. 2). Hamari and Järvinen (2011) explain that game mechanics are crucial for having fun while playing the game or engaging in the activity. This task of choosing and developing game mechanics that engage user is the responsibility of game designers.

Mechanics are purpose-built, which means that the use of those mechanics supports the general objective of the service. "[T]hey are either used for pursuing the goals, or the game as a system is using them for giving feedback to the player in relation to the goals" (Hamari & Järvinen, 2011, p. 353). Attali and Arieli-Attali (2015) explain that game mechanics can have different effects on users depending on whether they support the extrinsic or intrinsic motivation. They recommend to characterize game mechanics, such as points and badges, as extrinsic rewards for a successful completion of a task (Attali & Arieli-Attali, 2015).

One main problem, which Robson et al. (2015) point out, is that gamification will fail if the concept is not elaborated. It is necessary that developers understand its benefits, challenges, and the varying interaction possibilities between game elements and users which, in the end, will lead to the desired behavior or outcome. Hamari (2017) points out that empirical evidence on the effectiveness of gamification is rather minor. Another problem related to the effectiveness of gamification appears to be the fact that a lot of studies on this topic are not homogenous or do not focus on an empirical research to confirm the effectiveness of gamification in general. Apart from mentioned problems, the different player types can affect the received emotions or triggered motivation as well. Hamari and Tuunanen (2014) show different definitions by authors related to player types, such as the one from Bartle (1996), namely, "Achiever," "Socializer," "Explorer," and "Killer." Considering the presented definitions and understanding of gamification and differentiation between game mechanics and dynamics, the next subchapter offers an overview of game mechanics and their characteristics.

4.2.1 Gamification Mechanics

For this investigation, the following game mechanics implemented in the fitness tracking applications were evaluated:

- *Goals*: clearly defined goals are necessary to know what a user is supposed to achieve (Kapp, 2012).
- *Points*: show user's progress during the game (Kim, 2015), and depending on the point system, they can reflect the earned skills, or they show the difficulty of the tasks during the ongoing game (Zichermann & Cunningham, 2011).
- *Levels*: show progress while doing and successfully finishing tasks (Kapp, 2012). The use of levels might increase player's ego-oriented attitude (Zichermann & Cunningham, 2011). Levels are often linked to experience points and the higher the level, the more points can be received. This creates a feeling of mastery and accomplishment (Kapp, 2012).
- *Progress Bars*: enable the monitoring of one's progress. They can engage users and show how much effort is needed to reach the next level or to fulfill the task (Zichermann & Cunningham, 2011).
- *Feedback*: offers clear information (how far away a user is from a goal) based on a current situation (Kapp, 2012; Zichermann & Cunningham, 2011). This enables to "evoke the correct behavior, thoughts, or actions" to fulfill the task (Kapp, 2012, p. 36).
- *Documentation*: creating an overview of (historical) data of all activities, which may be motivated by intellectual curiosity (Blohm & Leimeister, 2013).
- *Badges*: represent succeeded achievements. They make the achievements or skills more impressive (Sailer, Hense, Mandl, & Klevers, 2013). Besides visible badges (achievements), there are invisible ones as well, which can trigger curiosity to explore and find more badges (Hanraths, Wintermeyer, & Knautz, 2016). Buchem, Merceron, Kreutel, Haesner, and Steinert (2015b) define use of badges in two ways, as a trigger and as an award. Badges can also support social interaction, for example, when they are awarded for likes and post.

- *Leaderboards*: are visualizations of a ranking/scoring system among users (Kapp, 2012). Usually, they include the user name and the reached score (Zichermann & Cunningham, 2011).
- *Time*: can be defined as a motivator, for example, in the form of a countdown. It increases not only the stress level but the motivation and need to succeed in a task (Kapp, 2012).
- *Quests*: are specific tasks for which the user can receive, e.g., experience points, and which are usually used in educational context as they "contain the learning content" (Hanraths et al., 2016, p. 850). For the purpose of this research, we use the term "Challenges" instead of "Quests" as the evaluated applications apply this terminology.
- *Avatars*: are a general visual representation of users within a game and are not necessarily used to characterize the attitudes of a user (Hanraths et al., 2016).
- *Storytelling*: is narrative content (e.g., prologue, epilogue) that is defined as an atmospheric element. Storytelling elements may be crucial to understand how to solve a task or why to do it at all (Hanraths et al., 2016; Kapp, 2012).
- *Community Features*: include the possibility "to stay up to date through following [...] or befriending function" (Scheibe, Göretz, Meschede, & Stock, 2018)(Scheibe & Zimmer, 2019, p. 1488).
- *Rules*: describe the conditions of a "quest"/challenge and how achievements can be achieved or, generally, how they are calculated (Kapp, 2012).

4.2.2 Gamification in the Domain of Health

Nowadays, gamification is used in various domains, starting with education (Attali & Arieli-Attali, 2015; Barata, Gama, Jorge, & Gonçalves, 2013; Hanraths et al., 2016) and business environments (Huotari & Hamari, 2012), through social live streaming services (Scheibe, 2018; Scheibe et al., 2018; Scheibe & Zimmer, 2019), right up to health management. There are many studies within the health domain, but to the best of our knowledge, none of them analyzes gamification elements within mobile applications of activity tracker providers. Mobile applications meant, for example, Fitbit and Garmin, and not fitness applications by third-party suppliers, like Runkeeper or Strava, for running or cycling. Koivisto and Hamari (2014, p. 179) explain that gamification can support the improvement of physical activity and name such services as "Mindbloom," "Fitocracy," "Zombies," "Run!," and "Nike+."

In their project "Fitness MOOC," Buchem et al. (2015b) concentrated on the gamification designs used in wearable enhanced learning. It "focuses on enhancing user engagement on five levels of design [...] with the aim of enhancing the daily fitness of senior users" (Buchem et al., 2015b, p. 9). (Buchem et al., 2015b) pointed out, although the results are not generalizable due to the sample size and focus on senior users, that gamification is a crucial element of the user engagement design. They reported positive effects of the use of gamification design elements such as a better orientation in the training program, increased motivation, and an enjoyable experience. As this was a long-term project with different stages, Steinert, Buchem, Merceron, Kreutel, and Haesner (2018) tested their "fMOOC@Home" in a subsequent 4-week study. All in all, their results showed significant health improvements.

A lot of studies (e.g., Chen & Pu, 2014; Chung, Skinner, Hasty, & Perrin, 2017; Ribeiro, Moreira, Barros, Almeida, & Santos-Silva, 2016; Walsh & Golbeck, 2014; Zhao, Arya, Whitehead, Chan, & Etemad, 2017; Zhao, Etemad, & Arya, 2016; Zhao, Etemad, Whitehead, & Arya, 2016) investigated already developed gamified systems promoting use of activity trackers or physical tracking in general. These studies mostly revealed positive effects of gamification, for example, that the implementation of gamification in health domain can result not merely in short-term engagement but rather in long-term improvement as well. One study showed that "based on existing technologies and user needs, the idea of employing wearable activity tracker for gamification of exercise and fitness is feasible, motivating, and engaging" (Zhao, Etemad, & Arya, 2016, p. 339). As the aim of the integration of gamification is to increase the motivation to be physically active, Zhao, Etemad, and Arya (2016) confirmed that users' engagement is linked to the integrated game elements and can improve the physical activity.

Nelson, Verhagen, and Noordzij (2016) thematized and analyzed aspects which motivate or rather empower users to reach their personal health goals. According to Walsh and Golbeck (2014), who did a controlled study (30 days) with 74 Fitbit-wearing participants who interacted with a specially developed web application ("StepCity"), games and social experiences can motivate users to take more steps and to be more active. Besides applications, Chung et al. (2017) investigated gamification in the health domain by using twitter and observing Fitbit users. Chung et al. (2017) developed a mHealth intervention (2 months) with overweight/obese and healthy (normal weight) participants that had to use a Fitbit Flex and twitter during the study. They integrated challenges such as 1-day or multiple-day challenge. The study revealed positive impact on the amount of steps taken during the day. Dadaczynski, Schiemann, and Backhaus (2017) analyzed the impact of gamification during a 6-week browser-based online intervention ("Healingo Fit") and using Fitbit Zips. They implemented a daily step goal, quizzes (knowledge about physical activity and general health), and the possibility to choose health goals (up to 3 out of 60 predefined goals). Dadaczynski et al. (2017) mentioned that tracking-based online intervention supports the increment of physical activity, e.g., walking. In their study "Gamification shows the greatest explanatory power in predicting health related experience of competency" (Dadaczynski et al., 2017, p. 7).

Barratt (2017) analyzed the application "Strava" and pointed out the positive effects the app had on cyclers. According to Barratt (2017, p. 335), "the research illustrates that a gamified fitness app and health tracker can be used successfully to enhance the activity of an engaged community of enthusiasts." Lister, West, Cannon, Sax, and Brodegard (2014, p. 10) confirmed that health applications "show an abundant use of gamification in health and fitness apps." Edwards et al. (2016) analyzed 1680 mobile health and fitness applications, and 64 of them use gamification elements. In the end, they investigated the 64 applications in order to gain some insights in the techniques of changing the human health behavior.

In a literature review, Alahäivälä and Oinas-Kukkonen (2016) showed that out of 15 studies on health interventions that included gamification elements, nine publications concentrated on increasing the physical activity. Johnson et al. (2016) did a systematic review of gamified health and well-being applications to analyze the effectiveness and quality of such applications. They identified 19 papers which revealed the effect of gamification in the domain of physical activity. The applied gamification elements were, for example, points, leaderboards, challenges, achievements, and levels. Generally, the most game design elements mentioned in the reviewed 19 papers were rewards, followed by avatars and leaderboards. A systematic literature review by Johnson et al. (2016, p. 104) showed that "gamification could have a positive effect on health and well-being, especially when applied in a skilled way." Ahola et al. (2013) also detected positive effects of the use of gamification, like increasing activity. Orji and Moffatt (2018) did an empirical review of 85 papers about persuasive technology for health and wellness. Here, again, the majority (92%) of the reviewed papers showed positive effects. "[S]ome of the technologies are aimed at reinforcing and strengthening existing behavior (e.g., increase daily step count [...]" (Orji & Moffatt, 2018, p. 78). Hamari and Koivisto (2013) investigated to what extent social factors (e.g., high-score lists, collection of points for social reasons like recognition) influence the acceptance of gamification or rather support the continued use of gamification elements. They investigated the application "Fitocracy," a gamified service for physical exercise. Hamari and Koivisto (2013) revealed that social aspects are an important and influential factor related to the acceptance and continued use of gamification elements. Additionally, Koivisto and Hamari (2014) empirically investigated the concept of gamification and its benefit related to demographic differences (age and gender) with "Fitocracy" as a case study. They showed that women perceived gamification elements and its influence related to social benefits stronger than men did.

4.2.3 Goal Orientation Theory, Flow Theory, and Self-Determination Theory

Gamification elements or the game mechanics can provoke certain game dynamics, hence, a desired behavior of users. Since each person is unique, the implemented game mechanics will not have exactly the same impact on all users. One theory about human motivation to engage in certain activities that was intensively researched in the context of sport and exercise psychology is the so-called goal orientation theory of achievement motivation (Cumming & Hall, 2004; Jackson, Ford, Kimiecik, & Marsh, 1998; Murcia, Gimeno, & Coll, 2008) and can help us determine which game mechanics might be more successful in influencing behavior of certain types of people. This theory is adequate for our study since it also focuses on human motivation (in our case induced by game elements). "[...] [M]otivation is a key ingredient in understanding behavior patterns as well as in determining the intensity and direction of behavior (Iso-Ahola & St. Clair, 2000)" (Murcia et al., 2008, p. 182). "Individuals' goal orientation will influence their definition of success, which, in turn, will impact their motivation to perform physical activity" (Cumming & Hall, 2004, p. 748).

In general, physically active people might have different perception of sport and its benefits. For some of us, these benefits are materialistic and individualistic (fame, fortune, recognition); for others, these benefits are "intrinsic to the activity itself (e.g., becoming physically fit)" (Duda, 1989, p. 320). This differentiation is also the basis of the goal orientation theory. On one hand, we find task-oriented people who, e.g., focus on personal improvement and mastery (Duda, 1989) and are more likely to "adopt a self-referencing criterion for evaluation" (Cumming & Hall, 2004, p. 748). On the other hand, we have ego-oriented people who are more competitive and focus on beating others, they "define success [...] in normative terms, such as outperforming others or being the best on a task" (Cumming & Hall, 2004, p. 748)(Duda, 1989). In terms of perceived ability, a task-oriented person tends "to believe that ability is reflected through effort and improvement," whereas ego-oriented person believes that "ability is expressed by outperforming others" (Murcia et al., 2008, p. 182).

In our study, we only focus on the mobile applications provided by fitness tracker manufacturers, and therefore, we do not have any insights into the goal orientation of the users (the dispositional component of the goal theory) and their actual change in motivation and behavior due to the usage of these apps. However, some researchers indicate that the so-called motivational climate (the contextual component) can influence the development of the goal orientation (Ames, 1992; Cervelló & Santos-Rosa, 2001; Ebbeck & Becker, 1994; Escarti, Roberts, Cervello, & Guzmán, 1999; Murcia et al., 2008; Nicholls, 1989; Pensgaard & Roberts, 2002). "Parents, coaches, teachers and peers can all influence the motivational climate which can also be of two types: a mastery or task-oriented motivational climate and a competitive, or ego-oriented, motivational climate (Ames, 1992)"(Murcia et al., 2008, p. 182). Therefore, we suggest that the mobile fitness applications together with the fitness community that can be reached through these applications constitute such motivational climate. During evaluation of the apps, we will try to classify the implemented game mechanics as fueling either a competitive or a mastery/task-oriented motivational climate.

The different goal orientations of the users together with the different motivational climates can lead to diverse behavioral consequences and experiences, one of which is the so-called flow (Jackson & Marsh, 1996; Murcia et al., 2008). Jackson and Roberts (1992) examined the role of goal orientations and perceived ability as psychological correlates of flow states "[. . .]. Relationships were found between endorsement of task involvement, high perceived ability, and frequency of flow experiences" (Jackson et al., 1998, p. 359). The concept of flow was coined by Csikszentmihalyi (1975), who explained why individuals engage in free time activities (e.g., sports). "[H]e defined the 'optimal performance state' as the extensive engagement in a specific task with a feeling of pleasure" (Türksoy, Altıncı, & Üster, 2015, p. 302).

Why is the flow theory important for our research? "Experiencing frequent flow states within a specific activity leads to a desire to perform that activity for its own sake; that is, the activity becomes autotelic (Csikszentmihalyi, 1975, 1990)" (Jackson et al., 1998, p. 359). Hence, a frequent flow state during an activity (e.g., exercise) can lead to the desire to perform it for its own sake (behavioral change would indicate that the person "learned" to be more active). In the game and gamification context, the state of flow is an important part of the user experience (Buchem, Merceron, Kreutel, Haesner, & Steinert, 2015a). But also in sports, this is a very relevant motivational factor: "[. . .] athletes in a flow state are known to demonstrate greater commitment to the activity, to be more intrinsically motivated, and to demonstrate greater persistence in their sport practice, each of which reduces the likelihood of sport dropout (Jackson & Marsh, 1996)" (Murcia et al., 2008, p. 182). The autotelic experience witnessed during the flow was "described by Csikszentmihalyi (e.g., 1990) as an intrinsically rewarding experience. Deci and Ryan (1985) describe flow as a purer instance of intrinsic motivation" (Jackson et al., 1998, p. 360). Hence, an autotelic state strongly connected to flow experience leads us to the next theory, which also becomes an integral part of this study, the self-determination theory SDT.

Deci and Ryan (1985) distinguish between three types of motivation: the inner motivation (intrinsic), external motivation (extrinsic), and lack of motivation (amotivation). The intrinsic motivation is given "when the individuals involve in an activity they are interested in or feel pleasure doing it. On the other hand, individual with external motivation involves in an activity to achieve distinguishable results (Lonsdale, Hodge, & Rose, 2008) [. . .]. Those with lack of motivation can feel incompetency or lack of control (Pelletier et al., 1995)" (Türksoy et al., 2015, p. 302). This could mean that people who are intrinsically motivated should be more likely to experience flow since they are interested in the task at hand (Deci & Ryan, 1985; Jackson et al., 1998). "The intrinsic needs for competence and self-determination motivate an ongoing process of seeking and attempting to conquer optimal challenges (Deci & Ryan, 1985, p. 32)" (Jackson et al., 1998, p. 361), which in turn reminds us of the task-orientation of the users as well as the mastery or task-oriented motivational climate. According to Csikszentmihalyi (1988), individuals with an autotelic personality might indeed have a greater tendency to experience flow, since they are able to "enjoy the process of engagement without concern for extrinsic rewards (Mandigo & Thompson, 1998)" (Murcia et al., 2008, p. 182), they focus on the task rather than on the anticipated outcomes (Jackson et al., 1998). The importance of task-orientation for the flow experience was already mentioned by other researchers: "(Kimiecik & Jackson, 2002) discovered that the task goal orientation was the best predictor of flow in sport. Recent research has also revealed that the dispositional flow state correlates positively and significantly with self-efficacy, the tendency toward a task orientation, and the perceived value of physical activity (Tipler, Marsh, Martin, Richards, & Williams, 2004)" (Murcia et al., 2008, p. 182).

Still, autotelic personality (or task-orientation) of the users together with task-oriented motivational climate do not necessarily lead to a flow experience and subsequent behavioral change. Another important aspect mentioned by many researchers is the (perceived) abilities or skills of the users:

> "[. . .] both challenges and skills must be relatively high before anything resembling a flow experience comes about. Importantly, we focus on 'perceived' sport ability, because within the flow model 'it is not the skills we actually have that determine how we feel, but the ones we think we have' (Csikszentmihalyi, 1990, p. 75). This provides the basis for the notion that high perceived ability may be a necessary precondition for flow states" (Jackson et al., 1998, p. 361).

In order to reach the flow experience, one's perceived skills and the challenge need to be in balance. The orthogonal model of flow theory by Csikszentmihalyi (1982) indicates what can be the result of an imbalance. When the perceived skills of an athlete exceed the perceived challenge of the activity, then he or she will experience relaxation. In turn, when the challenge outweighs the perceived skills, the athlete will experience anxiety. Finally, when challenge and skills are perceived as low, the athlete will experience apathy (Stavrou, Psychountaki, Georgiadis, Karteroliotis, & Zervas, 2015). Only "[w]hen the challenges and skills are perceived as being in balance, the person enjoys the moment and stretches his or her capabilities to learn new skills and increase self-esteem and personal complexity" (Stavrou, Jackson, Zervas, & Karteroliotis, 2007, p.439). What does this mean for fitness app developers? How can they prevent user's amotivation toward their product? In order to develop an application that motivates users to exercise and actually change their behavior in the long term, the implemented game elements, especially challenges, would need to be adjusted to user's perceived abilities. Too easy tasks will not challenge the users and may lead to relaxation and boredom, whereas too challenging ones can cause anxiety. Both a bored user and a stressed and anxious one are less likely to continue using the applications or be somehow influenced by it. In turn, a user who is being challenged, but also gets sense of achievement, is more likely to experience flow and carry on using the application.

4.3 Methods

The aim of this study is to detect and compare gamification elements in the analyzed fitness tracking applications and implicate which behavioral dynamics they can evoke, to finally conclude whether the implemented user engagement design (game mechanics) supports long-term engagement and learning to be physically active. First, the most popular fitness trackers were detected. The focus of this investigation was set on the top ten activity trackers and their applications. This amount of applications is assessable to report in detail and still constitutes a representative overview as it includes manufacturers that were omitted in scientific studies until now. For the content analysis, conducted during September–October 2018, we used the versions of the applications that were current at that time. We referred to the four-eye principle to analyze the game mechanics of the applications thoroughly and to warrant objectivity. Before coding the game mechanics included in the applications, we referred to literature on gamification to acquire a better understanding of the concept and its elements. The insights that we gained are summarized in the literature review. The coding process was iterative. In the first round, both authors coded independently of each other based on the acquired knowledge. For each application, coders created a user account. The comparison and discussion of the results enabled the researchers to prevent any ambiguities and to adjust the definitions of game mechanics to the objects of the study. In the second round of the analysis, the criteria were more accurate for the fitness tracker applications and led to removal or addition of further relevant game mechanics. Table 4.1 shows the results of this process and serves as a codebook. It includes the relevant game mechanics and their respective definitions. One of the elements could not be accurately evaluated ("Feedback") as this would require connecting the respective device. For current analysis, the notification settings within each application were used as an indicator for giving such feedback. Furthermore, the game element "Rules," as defined in Chapter 4.2.1, was not included in the analysis as in the context of fitness tracker applications. This element is not very elaborated and the outcomes would be redundant with the outcomes for "Clear goals" or "Challenges." All investigated challenges are necessarily defined by rules (e.g., number of competitors, time constraints); the same holds for clear goals (e.g., how many steps need to be reached within 24 hours).

Table 4.1: Definitions of game mechanics related to applications of fitness tracker

Game mechanics	**Description**
Points	Points that are not related to a specific challenge, they reflect the overall performance of the user and are necessary to level up.
Leaderboard	Lists of users (friends, strangers) ranking them according to a specific criterion (total steps, distance, etc.).
Badges	Visualization of achievements; can be received for successfully accomplished challenges or for reaching a milestone; may contain title, description, date of receiving, etc.
Levels	Show the overall advancement of the user since using the app (not related to a specific challenge or short-term goals); are estimated based on points that the user receives for different activities; usually displayed in user profile.
Story/theme	Narrative elements, e.g., theme, motto, prologue, epilogue, additional information during a challenge.
Clear goals	For example, number of steps, distance/meters to achieve, number of activities, daily step goal, or other daily goals.
Feedback*	Notifications during a physical activity, reminder of the (clearly defined) goal; also notification when the goal was reached; notifications on smartphone, not only the tracking device.
Progress	Visualizations which show, for example, how many steps, points, etc. are missing to reach the goal/next level.
Challenges	Tasks setting clear goals for a user; can contain time constraints; can include group challenges leading to an inter-user competition.
Documentation	Documentation of physical activities, statistics, general overviews.
Time Pressure	Time constraint for challenges or goals (e.g., daily step goal).
Avatars	Possibility to choose a profile picture and a nickname; a personalized icon, for example, during challenges or on leaderboards.
Community Features	Possibility to connect with friends within the application.

**Note:"Feedback" in form of notification on the phone and not on the wearable tracking device.*

4.4 Results

The results of the analysis are listed in Table 4.2. The most gamification elements were implemented in Samsung Health, Garmin, Fitbit, as well as Withings Health Mate, Apple Activity, and Moov Now. The identification of game elements appeared difficult regarding few cases. The deeper analysis of Moov Now shows that the wearable device might offer a possibility to endorse people who are already sporty or even more active than an average person. Therefore, Moov Now's levels are different than the ones applied by Garmin or Samsung Health. Moov

Now's levels are not completed through collection of points or challenges but rather through finishing a workout and improving the own performance. Furthermore, in this investigation, "Clear goals" mean, e.g., daily step goals or the count of exercises one would like to accomplish weekly. Moov Now provides various workouts including certain requirements and defining clear tasks and subsequent goals (which is a short-term goal); however, these are not directly comparable with, e.g., a clear goal of doing at least 10,000 steps per day (which through a long-term repetition can lead to a learning effect). Furthermore, unlike virtual worlds in the gaming context, stories/themes found within the fitness tracker applications were very simple. The only two examples are Fitbit and Samsung Health, which included a kind of background stories in some of their challenges. Finally, it was not possible to define clear goals (e.g., 10,000 steps per day) in the Polar Flow application but only general activity goals that are not apparent for the user. Furthermore, it was possible to connect with friends, but only through third-party applications.

The mostly applied gamification elements in the investigated applications were documentation (usually historical overview of physical activities and sleep), avatars (profiles with profile pictures), clear goals, progress (toward these goals), and time pressure (usually linked to clear goals that need to be achieved within 1 day or 1 week). The top three gamified fitness tracker applications, based on this categorization, are Samsung Health, Garmin Connect, and Fitbit (Table 4.2).

Table 4.2: Overview of implemented game mechanics related to the fitness tracker applications: (1.1) Health, (1.2) Activity, (2) Fitbit, (3) Garmin Connect, (4) Amazfit, (5) Moov Coach, (6) Health Mate, (7.1) Polar Beat, (7.2) Polar Flow, (8) Samsung Health, (9) TomTom Sport, and (10) MiFit

Game mechanics	1.1	1.2	2	3	4	5	6	7.1	7.2	8	9	10	Total
Points				•						•			2
Leaderboard			•	•		•	•			•			5
Badges		•	•	•		•	•			•			6
Levels				•		(•)				•			3
Story/theme			(•)							(•)			2
Clear goals		•	•	•	•	(•)	•		(•)	•	•	•	10
Feedback			•	•			(•)			•			4
Progress		•	•	•	•	•	•		•	•	•	•	10
Challenge		•	•	•			•			•			5
Documentation	•	•	•	•	•	•	•	•	•	•	•	•	12
Timepressure		•	•	•	•	•	•		•	•	•	•	10
Avatars		•	•	•	•	•	•	•	•	•	•	•	11
Community features		•	•	•		•	•		(•)	•		•	8
Total	1	8	11	12	5	9	10	2	6	13	5	6	

4.4.1 Samsung Health

The Samsung Health application includes the most gamification elements. The content analysis showed that Samsung focuses more on creating a competitive and ego-oriented climate.

In particular, there are four different elements that seem to mostly address the competitive type of users and support increase of their physical activity. The first feature is the "steps leaderboard," a global ranking where one's performance is set into relation to the performance of all users as well as one's respective age group. Furthermore, the leaderboard includes ranking of the user and his or her friends (Figure 4.1 (1)). The second element is the global challenges (Figure 4.1 (2)), which are topical monthly challenges (story/theme element), e.g., "Tomato, September" or "Avocado, October." Here, one has the possibility to compare oneself with all participating Samsung Health users (Figure 4.1 (3)) (e.g., the Tomato Challenge had 1,392,086 participants) by making over 200,000 steps within 1 month. The challenge contains a walking path divided into several stages that need to be completed within a limited period of time (time pressure). Upon completion of each stage, the participant receives an orange star. Furthermore, there are health missions for which one can get bonus challenge points. There are also bonus points for being in the top 30%, top 10%, as well as top 3 participants. Each challenge has a dedicated animal that shares different information with the participant during the challenge.

The third feature is the possibility to create a 1:1 challenge with a friend (Figure 4.1 (4)). The challenger defines a step goal (10,000, 30,000, 50,000, 70,000, and 100,000 steps) to reach within a specific period of time. The user who reached this goal first wins.

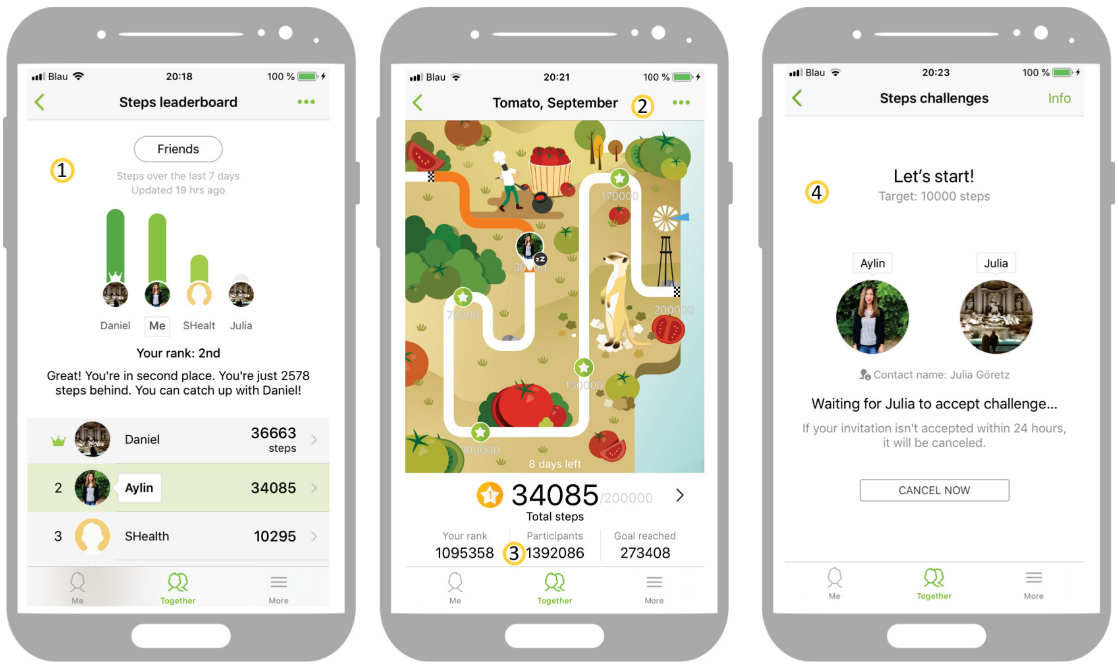

Figure 4.1: Screenshots of the Samsung Health App (I)

Finally, Samsung Health is working with experience points (XP), which are called "challenge points" and are necessary to level up (Figure 4.2 (5)). The "Challenge levels" reflect the challenge experience of the user. On each level, a respective description is assigned to the user: "Newbie," "Achiever," "Expert," "Master," and "Champion" (Figure 4.2 (7)). A progress bar for each challenge level shows how many experience points the user needs to reach the next stage (Figure 4.2(5)). Additionally, the profile picture is distinguished with wings graphically reflecting user's progress (Figure 4.2(6)). For users who would like to present themselves within the community, this could satisfy their need for self-presentation. According to Samsung Health, the benefits of the challenge level are to "[c]ompare challenge level with friends," "[g]et a special level title and symbol," "[c]hallenge friends who are at similar levels," and "[j]oin an event or promotion" (Samsung Electronics Co., Ltd., 2015-2016). Samsung Health also suggests that in order to level up fast, one should "[c]hallenge a friend who has a higher Challenge level" (Samsung Electronics Co., Ltd., 2015-2016). Here, the user is being provoked to compete with users/friends who might be more physically active. Depending on the particular case, the user can be either sufficiently challenged (when the gap in physical ability is not too big) or demotivated (when the divide is too significant). Another aspect that can either motivate or repeal users is the display of number how many times a user had won, lost, or withdrawn from a challenge (Figure 4.2(8)). With those game mechanics, it seems that the Samsung Health application creates are more competitive and ego-oriented climate.

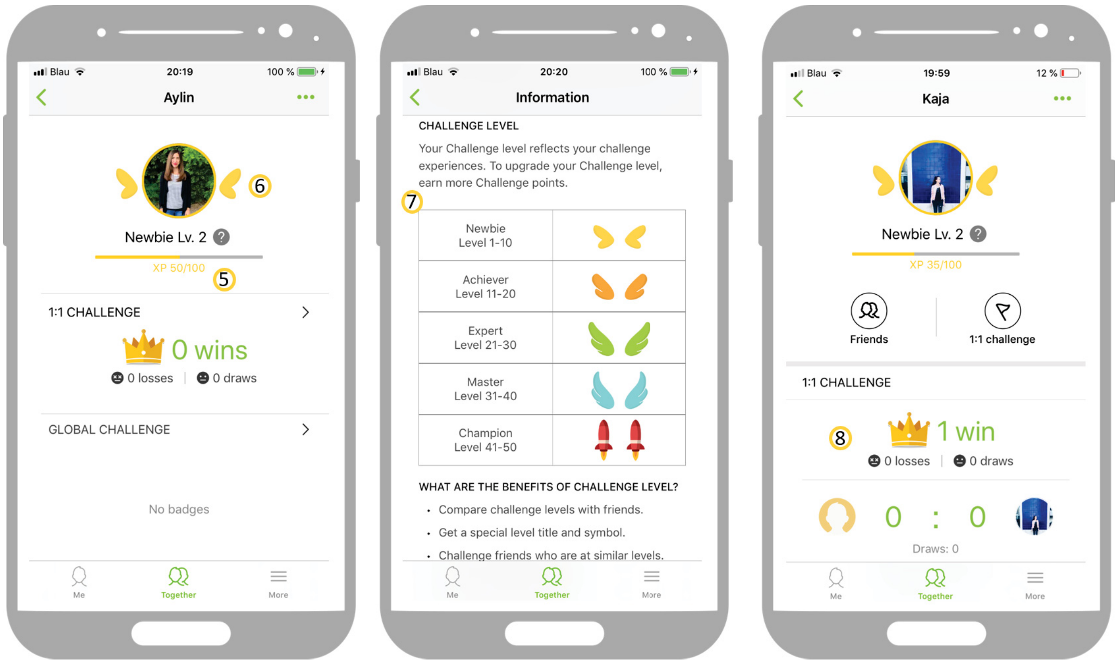

Figure 4.2: Screenshots of the Samsung Health App (II)

Apart from the leaderboards and challenges, it is possible to receive badges (rewards) as well. However, the badges remain hidden until their receipt. This means that users cannot see or work toward earning a specific achievement (badge). It is possible to receive badges for different breakthroughs, e.g., sleeping well, for reaching a daily step goal, or achievements in global challenges (e.g., the best explorer or reaching the step goal).

Finally, activity trackers should encourage users to be more physically active as well as raise awareness for one's health and well-being. Samsung Health enables it by providing overview of the progress toward a clear goal (categorized here in activity, nutrition, and sleep). The user can record diverse activities, heart rate, meals, weight, as well as water or caffeine intake. The app shows a clear overview and summary of the data over weeks for user to reflect on.

4.4.2 Garmin Connect

Garmin Connect offers many game mechanics. For example, it awards achievements (badges) categorized into seven different groups: steps, running, cycling, activities, health, challenges, and "Garmin Connect Features." These categories may appeal to different user types. Users who would like to be more physically active can focus on step badges. Those badges are connected to clear goals, for example, exceeding yesterday's step goals. We assume that the badges have a progressing pattern. The amount of points that one can earn with a badge is increasing, while the objective itself is also becoming more challenging. For example, after the badge for "3-Day Goal Getter" (achieving the daily step goal 3 days in a row) for 1 point comes the badge "7-Day Goal Getter" (hitting the daily step goal 7 days in a row) for 2 points. There is no predefined order showing which badge has to be received first, but if a user starts to be physically active and would like to increase the activity levels gradually, earning badges by participating in challenges with increasing difficulty could be helpful. The badges are visible and include clear goals, which might not only be challenging but could also increase the level of activity in the long term by inducing the feeling of flow.

With task badges, Garmin might motivate users enjoying social aspects or interacting with the application itself. Task badges also enable users to earn points (Figure 4.3 (1)) and level up (Figure 4.3 (2)); therefore, the feeling of flow may be maintained. For example, it can happen that users are not motivated enough or are not in a good mood or too tired to do few more steps and reach their daily goal. Before they get frustrated by not achieving the daily objective and not getting any points, they can share or like content, change the profile picture (once), and this way receive, e.g., 1 point. This way the frustration on less active days leading to possible amotivation in using the application can be prevented.

Another way of avoiding user's frustration is the filtering function in the overview of all badges. Thereby, a user can decide if he or she only sees less difficult badges/challenges for 1 or 2 points (which seem more reachable), or also badges for 4 or 8 points (which, for some people, can be also motivating when, e.g., they are spurred by ambition).

Some badges can be received only once. This is an interesting method to encourage the progress of the user as well as flow that he or she experiences. Hereby, one is forced to try to reach another, possibly more challenging goal or otherwise one will stop earning points and cannot reach the next level. From the flow theory perspective, this way the user remains challenged and does not get bored. If we consider the intrinsic motivation to accomplish or to learn something new, badges with clear goals and increasing difficulty may create a task-oriented climate. Nevertheless, they can also offer an ego-oriented and competitive component, since the points that can be received increase user's level, which together with acquired badges can be seen by user's friends on his or her profile. Furthermore, Garmin offers a leaderboard (Figure 4.3 (3)). Additionally, the ego-oriented competitive climate is fueled by the fact that the own achievements can be directly compared with achievements of a friend (Figure 4.4 (4)) in a juxtaposition.

There is a difference between seeing only friends' achievements within their collection/profile

(Figure 4.4 (5)) or seeing a direct comparison of the performance (Figure 4.4 (4)). Finally, Garmin Connect offers the possibility to create own challenges, which can be predefined by the activity (e.g., steps, cycling, swimming, etc.), duration (a day challenge, weekend challenge), and number of competitors (Figure 4.4 (6)).

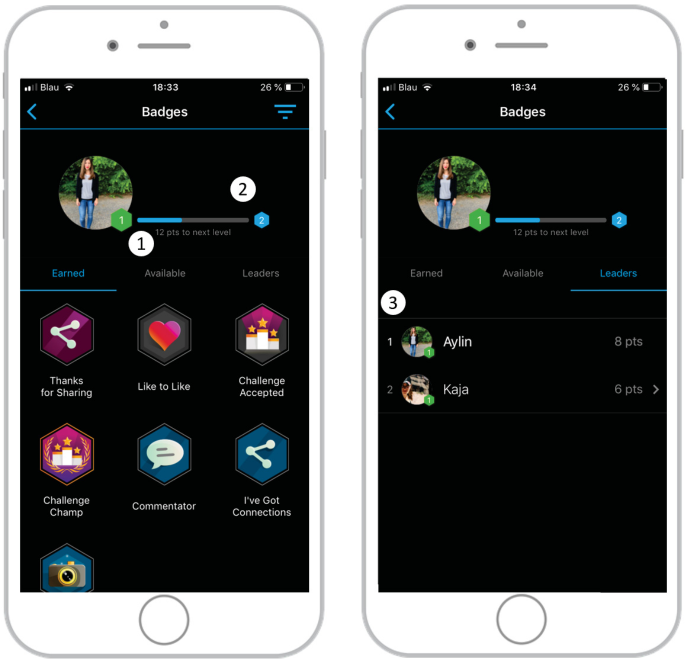

Figure 4.3: Screenshots of the Garmin Connect App (I)

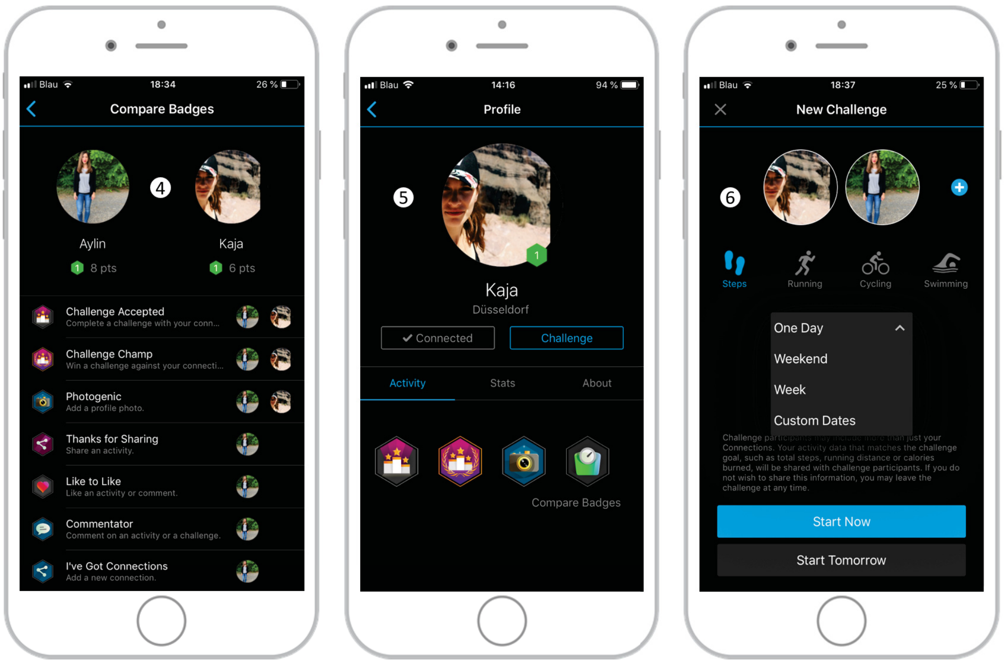

Figure 4.4: Screenshots of the Garmin Connect App (II)

4.4.3 Fitbit

Fitbit is the third application with most game elements. It appears that Fitbit is creating both an ego-oriented (competitive) and a task-oriented (mastery) climate. For ego-oriented people, it can be motivating to use the challenges (Figure 4.5 (1)) and the "friends" leaderboard. Game mechanics such as challenges trigger competitive dynamics, e.g., wanting to be the best. Apart from such inter-user competitions, there are three types of "Solo-Adventure" (Figure 4.5 (2)) challenges which may be more appealing for task-oriented people. The multiplayer challenges (2–10 people) have different time restraints. The "Daily Showdown" lasts for 24 hours, while "Workweek Hustle" lasts for 5 days. Here, the focus is set on the step count and ranking of the participants. Additionally, the users can communicate within a challenge messenger screen window. Another type of multiplayer challenge is the adventure challenges (Figure 4.5 (3)) that relocate competitors into a virtual geographical world (virtual world, story/theme aspect), for example, to the "Pohono Trail" (62,500 steps) or "Valley Loop" (35,800 steps).

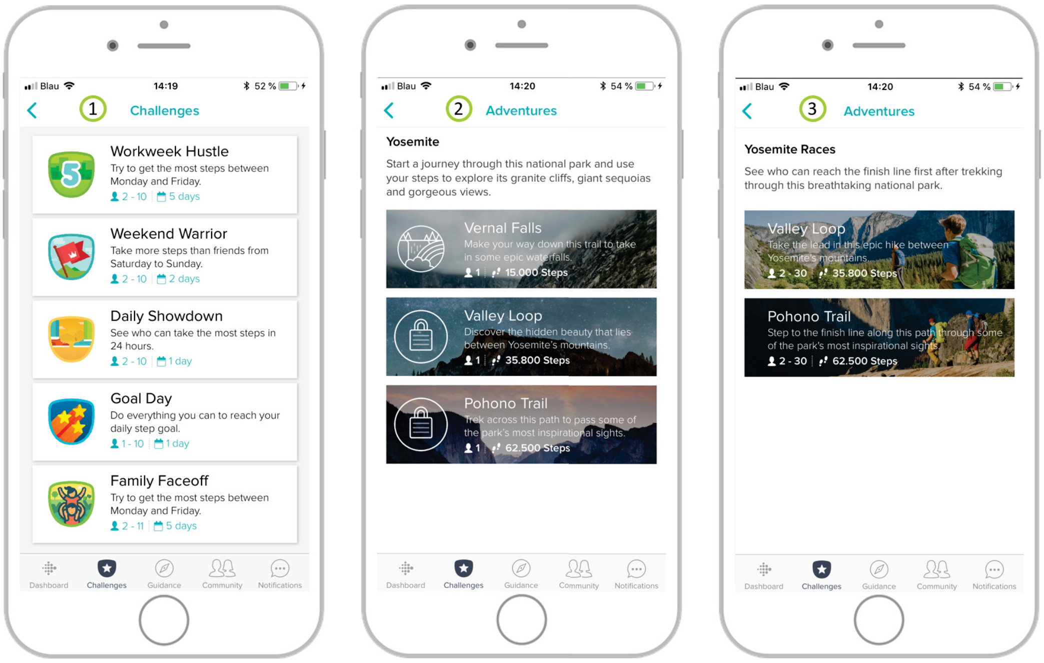

Figure 4.5: Screenshots of the Fitbit App (I)

During the challenge, it is possible to receive narrative information about the location and to unlock, for example, panoramic photos. As for the rules of multiplayer adventure challenges, winner is the one who reaches the predefined count of steps first. All challenges include feedback, e.g., that a user tiptoed or overtook another user or that the step goal is completed. During a challenge, Fitbit sends many notifications of this kind within the challenge chat window. It also informs other participants when, for example, one of the users reached a daily step goal or got an achievement. Extrinsically motivated people can be motivated by these game mechanics (challenges, feedback, and competition). Furthermore, challenge participants have the possibility to write messages and cheer others on. It is possible, that when all participants in those challenges are similarly skilled (in this case, equally physically active), they will experience flow and enjoy the challenge. The feeling of flow can be maintained as long as the challenge is dynamic through frequent ranking/position change of the participants and when there are only minor gaps between their performances.

All introduced challenges set clear goals for the users, e.g., to be the first to reach a predefined amount of steps. During the challenges, users get different kinds of feedback on their progress, e.g., competitive notifications within the challenges or virtual places, or simply the number of steps left to reach the daily goal. Apart from the challenges, the user can accept the predefined daily step goal of 10,000 steps or define an own objective. Also here Fitbit sends notifications to user's smartphone or the wristband informing him or her how many steps are missing to reach the daily step goal. The user can also check the overall progress overview (Figure 4.6 (4)) of his or her activity and access statistics from previous weeks (Figure 4.6 (5)). This constitutes a more task-oriented environment.

Apart from an ego-oriented or competitive climate, Fitbit's application also offers a task or mastery environment, where the main aim is not being better than others but to master an exercise and work on self-improvement. When people want to focus more on the task or activity itself instead of external factors, they can use Fitbit's "Cardio Fitness Score." This is a score bar (Figure 4.6 (6)) reflecting the fitness level of a user. If a user is getting fitter, the value on score bar will be higher; when his or her physical activity stagnates, it will decrease.

Figure 4.6: Screenshots of the Fitbit App (II)

Another element that might appeal to both task-oriented and ego-oriented users is the achievements/badges (Figure 4.7 (8)), which, in Fitbit, remain hidden. A user gets one when he or she reaches a certain milestone, however, without knowing them in advance. Those achievements are categorized as badges, for example, "Daily Steps," "Daily Climb," "Lifetime Distance," "Lifetime Climb," "Weight Goal," or "Challenge." It is possible that users who are interested in exploring new elements will be engaged in more physical activity (usually walking) in order to receive new, unknown badges, e.g., for every additional 5000 steps per day. This could enhance the feeling of flow as well. Another category of achievements is "Trophies" that, unlike badges, are visible from the beginning to the user. Both badges and trophies that a user received are displayed on his or her profile. By offering and rewarding badges (Figure 4.7 (8)) and trophies (Figure 4.7 (7)), Fitbit creates both task-oriented and an ego-oriented/competitive climate. The users have the possibility not only to collect achievements (as a way of self-fulfillment or just for fun), but also to share the earned badges and trophies with others. Additionally, during challenges, Fitbit informs all participants of badges or trophies that the user earned. Fitbit users have a profile with a picture that lists all their rewards and friends. They can hide their badges and trophies or leave it public for others to see. When seeing friend's achievements, one can feel motivated to earn such badge or trophy as well.

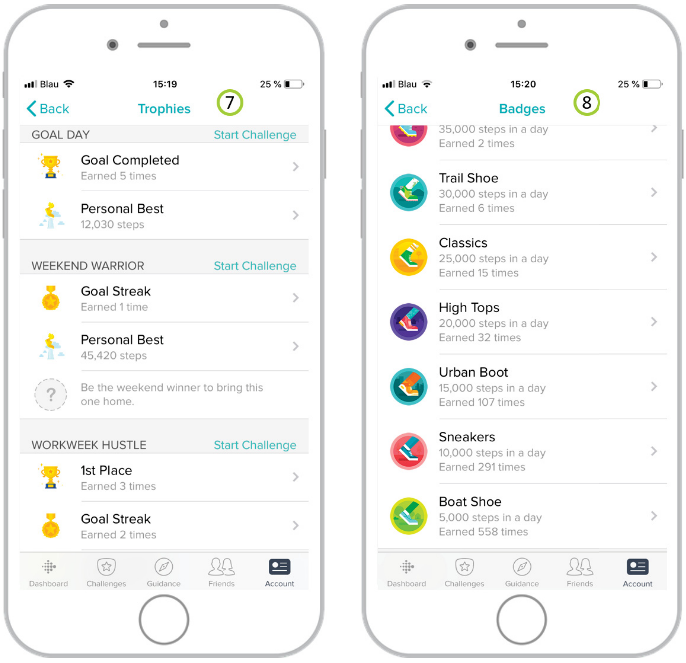

Figure 4.7: Screenshots of the Fitbit App (III)

4.5 Discussion

In this investigation, we analyzed applications provided for ten fitness trackers and the game mechanics that they contained. Previous literature revealed that gamification can help to increase user's motivation and encourage higher engagement with a service. Following this reasoning, we hypothesize that gamification elements within activity trackers and their applications can improve the physical activity of people in the long term.

To the best of our knowledge, no previous studies analyzed or compared the gamification mechanics of activity trackers' applications. We are aware that empirical research is necessary to better understand effects of gamifications and its impact on user behavior in context of activity trackers. This study, however, was an important first step laying out theoretical background and summarizing the results of our content analysis of the applications. With this study, we would like to show that besides an increased implementation of gamification elements, the developers need to consider the dispositional components like users' goal orientation (ego-oriented or task-oriented), motivation (intrinsic or extrinsic) or amotivation, as well as adequate contextual components like the motivational climate (competitive/ego-oriented, mastery/task-oriented).

The analysis of the fitness tracker applications showed that the gamification elements are implemented in various ways. Interestingly, while some studies pointed out that leaderboards, challenges, and points are one of the core mechanics of gamification, it is obvious that this was not the case for our investigation. Some applications (Samsung Health, Garmin Connect, Fitbit, Moov Coach, Health Mate) offer leaderboards, so that the users can compare their performance among each other. Similar effect can be achieved through challenges (e.g., Fitbit, Garmin Connect, Health Mate, Samsung Health). Based on that comparison, a real competition can start when users try to beat each other. This may lead to change of the user's behavior so that he or she is able to be better than others. These behavioral changes are usually accompanied by emotions such as ambition or willpower.

This competitive climate, introduced and triggered by game mechanics being leaderboards or challenges, may especially influence the ego-oriented people. For them, this type of game mechanics can lead to the state of flow. Ego-oriented users are engaged in the activity just as a means to an end, which is enjoying the moment of outperforming others. However, these circumstances might not be the ideal requirement for learning progress, since the dispositional and contextual components at hand are ego-oriented and extrinsic. Duda (1989) and Cumming and Hall (2004) showed that ego-oriented people do not focus on the activity itself; instead, they concentrate on rewards or confirmation that they can gain. Those circumstances as well as the rewarding feeling are rather short-lived. This happens especially when the user has no real competitors and remains on the first place for a long time (his or her abilities exceed the task; hence, he or she is unchallenged), or the distance to other and better competitors is way too big (the challenge exceeds one's abilities; hence, the user is overchallenged). Furthermore, such under- or overchallenge can often lead to boredom or anxiety, which in turn can end in amotivation of the user to engage with the service. In consideration of the above, leaderboards and (group) challenges might not be the best motivation for task-oriented and intrinsically motivated people and lead to long-term engagement or behavior change. It is debatable whether users who are always on one of the top ranks continue to engage in the activity because they learned to be more physically active. Based on the literature overview, the answer would be that they do it because of the competitive climate. The physical activity (here, taking steps) is only a means to an end, namely, to be the best. Based on the SDT, the extrinsic motivation thrives on pressure and fear of failure but also social recognition and appreciation of one's performance. Some of investigated applications offer the possibility to share, like, and comment on activities or achievements. Those functionalities may boost extrinsic motivational needs as well.

It is more difficult to assign levels and experience points to a respectively triggered behavior. Experience points or skill points as well as levels reflect users' ability and progress. For example, the badges of the category steps from Garmin Connect can ensure that a user is getting more physically active and keeps up the own progress. Gagne (1977) pointed out that we can speak of learning when a change in behavior occurs over a period of time. For example, if a user usually does 15,000 steps a day and would like to try to reach 20,000 steps, it is possible that this progression will occur over a longer period of time and will require the user to adjust his or her behavior. These changes in everyday behavior could include dismounting the bus one stop earlier than usually or taking a slight detour on our way to school or work. If the user repeats these changes frequently enough (at first with the intention to reach the 20,000), they might become a habit and the behavioral change will remain permanent (and not only until reaching the step goal). This long-term change is, however, more feasible in a mastery climate, where the activity itself and the user are in focus. In a competitive climate the focus switches to competition and short-term (peak) performances (one-time effort to beat other participants), which does not support formation of habit and learning. Therefore, this type of game mechanics and motivational climate is favored by task-oriented and intrinsically motivated users.

These intrinsically triggered behaviors are more likely to lead to the state of flow. Furthermore, related to the intrinsic motivation, the autonomy to choose, for example, which task should be tried out (Garmin Connect) supports the intrinsic motivation, however, not if the goals are too demanding or, in contrary, too easy for one's abilities. The balance between skills and the tasks is therefore essential. This is why it is important to give users the autonomy to decide which goals with which difficulty they want to strive for. This can foster their motivation and reduce the risk of being overwhelmed or afraid of failure. A counterexample is levels and points that can be earned through challenges (e.g., Samsung Health). These points are more likely to foster a competitive climate. Here, the focus lies on beating others, being the best, and possibly earning some kind of social endorsement. Here, it is doubtful whether the activity leads to creation of new habits and, in general, learning.

It is necessary for the user to have a clear goal in order to achieve a long-term behavior change. Without goals (possibly not only short-term but also long-term goals), the user can lose focus and motivation. Progress bars support clear goals, since this way users get feedback on how far they are away from, e.g., their daily step goal. Some goals have time constraints, which, on the one hand, can increase the motivation and incite ambition but, on the other hand, may decrease motivation when users realize that it is not possible to reach the goal or are stressed by the time pressure (leading to amotivation).

Historical overviews of all activities and reached goals show the users their progress over time and might be especially appealing for task-oriented people. The possibility to evaluate one's progress and to explore how one's performance is getting better (or worse) can trigger curiosity and develop awareness for the evaluation and interpretation of collected data. Especially, these progress overviews are improving mastery climate as they only focus on the user and his or her performance, excluding any external aspects (performance of others, outcomes of competitions, etc.). Especially, the feeling of competence, to evaluate and recognize own progress and success, increases intrinsic motivation. Unless, it is possible to see the performance overview (or parts of it) of other users or to even share and post own performance within the community–this can create a more competitive climate, since this enables comparison with others and/or social recognition. Finally, achievements (badges or trophies) provide a wide range for discussion.

For users who enjoy collecting badges, such achievements can be motivating. They can maintain the state of flow as users are focused on performing the activities and change their behavior so that they can accumulate achievements (self-fulfillment). Even if the state of flow is maintained (which may be motivating and enjoyable), the progress of learning does not need to be given. In order to let the behavior patterns become a habit and learn in the long term, the achievements (badges) need to be associated with clear goals which support a thoughtful change of behavior over long period of time. In the end, users still have the possibility to share their achievements (social recognition), or see the badges and trophies of friends and compare them with own achievements (competition). Therefore, achievements in the form of badges or trophies can generate both mastery and competitive climate.

Game mechanics of the investigated fitness tracker applications show that there are many possibilities to motivate people to be more physically active, but the induced behavior change can usually be short-dated, instead of becoming a habit. The process of actual learning might depend on different factors, which are not limited to the gamification elements but include the dispositional motivation of users (extrinsic, intrinsic, task- or ego-oriented), their goals, skills, acceptance of an application, and, abstracting from our theoretical implications, the knowledge and general understanding of the principles as well as importance of physical activity and a healthy lifestyle.

4.6 Conclusion and Outlook

The investigation showed that most of the game mechanics were integrated in Samsung Health, Garmin Connect, and Fitbit. Except for Apple Health and Polar Beat app, all remaining applications included at least five of the investigated elements. The theoretical investigation implied that it is reasonable to create a mastery climate in order to improve the process of learning, hence, a long-term change of behavior concerning physical activity. Competitive atmosphere and extrinsic influence refer more to such needs as external approval, social recognitions, competition and the presentation of one's skills. These conditions, however, do not support long-term changes, because the incentives are only temporary, and sooner or later, the allure gets lost. Nevertheless, this does not mean that game mechanics creating a competitive climate are not beneficial; after all, they are motivating and make the activity enjoyable. The only question here is for how long and with what impact.

Referring to the gaming domain in general, one should take into consideration the different types of gamers. This means that some game mechanics might be more appealing for specific gamer types, such as the "Achiever" or "Explorer." This also shows that implementation of gamification elements is a very elaborate undertaking that requires more than incorporation of points, badges, or levels. This should be considered in the future research.

Our investigation has few limitations. In the future, it is necessary to conduct empirical research in order to derive and connect certain game mechanics to behavioral dynamics and intrinsic as well as extrinsic motivation. As a next step, we would like to quantitatively and qualitatively investigate how game mechanics cohere with behavioral dynamics. With the theoretical background laid out in this study, we would like to empirically confirm our implications. Furthermore, this study focused only on the fitness tracking applications. Consideration of the respective wearables and their interaction with the users (e.g., in the form of sound or vibration notifications) is a further necessary step to better understand how gamification and fitness trackers can teach the users to lead healthier lifestyles.

To conclude, the introduced and applied theories reveal that developers of wearable-enhanced learning environment need to consider the different needs and attitudes of users. Its effectivity is defined through the satisfaction of users and their continued usage of the service or product. However, the study also showed that there is no one right formula to develop such successful wearable-enhanced learning environment. Here, it might be advisable (1) to analyze the target group (e.g., task-orientated users, ego-orientated users, or both), (2) to set individually manageable aims adjusted to user's health and fitness level (e.g., with the help of fitness pretests), and (3) to integrate challenges and tasks with incrementally growing intensity, which in turn supports the shift from a task one needs to complete from time to time to a long-term healthy habit. Furthermore, considering the intrinsic motivation being a good foundation for long-term learning, a wearable-enhanced learning environment needs to satisfy such users' needs as autonomy (e.g., to choose own challenges or tasks, time goals), competence (e.g., for mastery-oriented people, the aims should be manageable and challenging, but not frustrating), and relatedness. While addressing several interconnected theories, this study showed how complex is the concept and implementation of a successful wearable-enhanced learning environment. This also explains why not every health or fitness tracker application might be suitable to induce long-term changes, hence, teach the users to lead a healthy and fit life.

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Part II

Information Behavior within Health and Fitness-Related Facebook Groups

5 Motivations to Join Fitness Communities on Facebook: Which Gratifications Are Sought and Obtained?

Ilhan, A. (2018). Motivations to join fitness communities on Facebook: Which gratifications are sought and obtained? In G. Meiselwitz (Ed.), *Social Computing and Social Media. Technologies and Analytics, (Lecture Notes in Computer Science book series* (Vol. 10914, pp. 50–67). Springer. doi: https://doi.org/10.1007/978-3-319-91485-5_4

Abstract *Activity trackers are providing their users data on health and fitness. They measure, for instance, heart rates, record exercises and sleeping quality, and display burned calories. On Facebook, there are many activity tracker- and fitness-related groups. Why are users of activity trackers joining and consequently using such groups? In order to answer this basic question two theoretical approaches are adapted. Firstly, the Uses and Gratifications Theory (U&GT) identified gratifications, which are sought and obtained – in our case within those Facebook groups. Secondly, the Self-Determination Theory (SDT) is used to understand if the activities of users are caused by extrinsic or intrinsic motivations. For the purpose of this study an online survey was developed and distributed in 20 activity tracker- or fitness-related Facebook groups. All in all, data from 445 participants, who all are group members and are using an activity tracker, were evaluated.*

5.1 Introduction

In recent years activity trackers attract more and more the attention of researchers, especially within the Human-Computer Interaction Human-Computer Interaction (HCI) community. They are not only focusing on technical improvements such as the enhancement of the measurement quality and the collection and visualization of the data (Choe, Lee, Lee, Pratt, & Kientz, 2014; Fan, Forlizzi, & Dey, 2012; Y. Lee, Kim, Rho, Kim, & Lim, 2015), they are doing studies on user-based research related to the use and non-use of activity trackers as well (Fritz, Huang, Murphy, & Zimmermann, 2014; Gao, Li, & Luo, 2015; Giddens, Leidner, & Gonzalez, 2017; Ilhan & Henkel, 2018). Communities or rather the social online setting is less investigated related to activity trackers. According to Y. Lee et al. (2015, p. 1206), "products and services that promote health-related behavior, such as activity trackers, have increased dramatically in the market, little attention has been given to their social influences, such as social reinforcement from mediators." Also Rooksby, Rost, Morrison, and Chalmers (2014) describe activity trackers as social tracking devices and not only as health devices collecting data. Y. Lee et al. (2015, p. 1213) show that "in social media, the participants tried to make ideal presentations of themselves and gain emotional support, such as attention and reputation, from their social media friends." The social environment supports not only participant's improvement of health behavior, it enables the emotional support (relief and motivation), too (Y. Lee et al., 2015). Users of activity trackers regularly have the possibility to upload their activity records to Facebook. Figure 5.1 shows that posts within Facebook groups can be diverse. The left part in Figure 5.1 shows a discussion starting from a question. A Facebook user is searching after activity tracker-related information and received information by other users. The right part shows an overview (Fitbit dashboard) of succeed goals (steps, miles, active minutes and burned calories). User6 is self-presenting her-/himself by posting the succeed aims; and User6 got positive feedback from another Facebook user (User7).

Figure 5.1: Posts of a Facebook group (anonymized); left: User1 needs information; right: User6 realizes her-/himself (screenshot of a Fitbit dashboard).

Within Social Networking Services (SNSs), here, Facebook, we are able to identify numerous different fitness and health groups. Why do activity tracker- or rather fitness-orientated users cooperate with such Facebook groups if activity trackers provide functionalities that enable the improvement of health and fitness? Do they need the social reinforcement, competitions, information, entertainment, self-presentation or the motivation for the perseverance of fitness aims? To answer those questions the contribution is based on the Uses and Gratifications Theory (U&GT) and on the Self-Determination Theory (SDT). The latter one "has increasingly become a basis for interventions in the areas of health- promotion and physical activity" (Ryan et al., 2009, p. 118). Ang, Talib, Tan, Tan, and Yaacob (2015) point out that U&GT is not sufficient to be able to comprehend why humans use and seek and obtain gratifications. Therefore, they used a mixed approach model (U&GT and SDT) for the analysis of online friendships (Ang et al., 2015). We agree that for a deeper understanding of motivational reasons and needs the U&GT supports the comprehension but is not per se sufficient or the only approach to understand completely the media use of individuals (Ang et al., 2015; Ko, Cho, & Roberts, 2005; Ryan, Rigby, & Przybylski, 2006). Therefore, our study combines the two theoretical frameworks (U&GT and SDT). The purpose of this study concentrates on the needs and motivational forces, why members of activity tracker- or fitness-related Facebook groups are using this SNS.

5.2 Theoretical Background: SDT and U&GT

Humans all over the world carry out activities caused by specific needs. The motivations to satisfy those needs have different backgrounds. The SDT (Deci & Ryan, 1985, 2000; Ryan & Deci, 2000b; Ryan et al., 2009) focuses on those backgrounds and point out that humans are doing something based upon intrinsic or extrinsic motivation. The former is limited to the activity itself. Individuals are doing something, because they are interested in it. There is no exterior influence or pressure. It is the activity itself which motivates individuals. The decision to do something is completely self-determined (Deci & Ryan, 2000; Ryan & Deci, 2000b). Extrinsic motivation describes the situational condition that activities are done, because they are expedient or an instrument to reach some values originating from the environment (Deci & Ryan, 2000). Extrinsic motivation has four subcategories, namely *external regulation, introjected regulation, identified regulation* and *integrated regulation*. These subtypes (Table 5.1) are built related to the strength of autonomy (self-determination) from own values recognized in the environment to fully controlled through exterior influence (Deci & Ryan, 1985).

External regulation means that a user joins a Facebook activity- or fitness-related group only, because others told him or her to do so. *Introjected regulation* is defined as the behavior to use those groups only out of the fact that other users and friends of activity trackers are using those groups, too. Otherwise, if they do not join and use them they get a worth conscience, because it seems as not supporting other participants. This kind of extrinsic regulation is "a partial internalization in which regulations are in the person but have not really become part of the integrated set of motivations, cognitions, and affects that constitute the *self*" (Deci & Ryan, 2000, p. 236). Even if *identified regulation* is more self-determined than *introjected* and *external regulation* it is still the activity itself which is instrumentalized to gain something. "[I]f people identified with the importance of exercising regularly for their own health and well-being, they would exercise more volitionally" (Deci & Ryan, 2000, p. 236). Here, *identified regulation* is defined as the importance to support and help other users of activity trackers, for example, to reach their aims by forcing the social solidarity or to answer questions. The strongest autonomous regulation related to the extrinsic subtypes is described as *integrated regulation*. It is still a kind of extrinsic motivation, because of the fact, that individuals are doing something "to attain separable outcomes rather than for their inherent enjoyment" (Ryan & Deci, 2000b, p. 73). Activities or adapted values conditioned by integrated regulation "have been evaluated and brought into congruence with one's other values and needs" (Ryan & Deci, 2000b, p. 73). Besides individuals who are doing something out of intrinsic or extrinsic motivation, there are individuals who are not willing to do something.

Ryan et al. (2009) describe three different reasons why people are feeling *unmotivated*: (1) lack of skills or knowledge to do an activity, (2) missing coherence between activity and desired results, and (3) missing interest (Ryan et al., 2009).

Table 5.1: Subtypes of extrinsic regulation (Ryan & Deci, 2000a, 2000b; Ryan et al., 2009)

Subtypes	Characteristics	Degree on Self-Determination
External	• Punishment, • Controlled rewards, • Compulsion.	Fully Controlled ● ○ ○ ○ Self-Determined
Introjected	• Predetermined consequences, • Worth conscience, • Partial internalization.	Fully Controlled ○ ● ○ ○ Self-Determined
Identified	• Identification with external values.	Fully Controlled ○ ○ ● ○ Self-Determined
Integrated	• Own values are coherent with exterior values, • Self-Endorsement.	Fully Controlled ○ ○ ○ ● Self-Determined

The U&GT is first used for traditional media channels and examines why people decide to use a medium and which *needs* should be satisfied (Katz, Blumler, & Gurevitch, 1973-1974, 1974; Kippax & Murray, 1980; Palmgreen & Rayburn, 1979; Rubin, 1983). This theory leads on Katz et al. (Katz et al., 1973-1974, 1974). U&GT is also applied to SNSs and other social media channels (Flanagin, 2005; Larose, Mastro, & Eastin, 2001; Leung, 2001). Hsu, Chang, Lin, and Lin (2015) point out that social media and their popularity triggers a lot of research attention, especially for the better understanding why people decide to use it (Hsu et al., 2015; Kim, Sohn, & Choi, 2011). Hsu et al. (2015) showed that the motives why people use social media are divided in two categories: Firstly, psychological needs and gratifications (C. S. Lee & Ma, 2012; Li, 2011; Park, Kee, & Valenzuela, 2009; Áine Dunne, Lawlor, & Rowley, 2010) and secondly, social interaction (Li, 2011; Park et al., 2009; Pempek, Yermolayeva, & Calvert, 2009). According to Quan-Haase and Young (2010, p. 351), the U&GT is one "of the more successful theoretical frameworks from which to examine questions of 'how' and 'why' individuals use media to satisfy particular needs."

Therefore, U&GT stressed out "that users of media are active and goal-oriented" and that the selected medium depends on the satisfaction of those gratifications which satisfied the needs (Hsu et al., 2015; Sangwan, 2005). The process of user's media use begins with a social and psychological need (Katz et al., 1973-1974). Such human needs lead to user's choice of a medium (e.g., Facebook) based on the expectation that the use of this medium can gratify the social and psychological need. Gratification is described as the behavior of seeking satisfaction of certain needs (Rosengren, 1974). The satisfaction of certain needs, and therefore the motivation of using a specific medium, here Facebook activity tracker- or fitness-related groups, is based on the categorization related to McQuail (1983), namely *information seeking, self-presentation, socialization, and entertainment*. Hsu et al. (2015) show that a lot of researchers worked with the four categories in the context of social media (Boyle & Johnson, 2010; Chen, Yang, & Tang, 2013; Ellison, Steinfield, & Lampe, 2007; Papacharissi & Mendelson, 2011; Shao, 2009). Besides seeking of gratification, gratification can be obtained as well (Greenberg, 1974; Katz, Haas, & Gurevitch, 1973; Palmgreen, Wenner, & Rayburn, 1980). Palmgreen et al. (1980) point out that sought gratification and the obtained gratification are not always the same. If an individual is searching for information he or she can obtain other aspects, too. The information content itself can be assumed entertaining as well. Additionally, the need of information can cause to keep in touch with other individuals to get specific information, too. Therefore, by searching information an individual can obtain social contacts (socializing) as well. Klenk, Reifegerste, and Renatus (2017) did research about fitness applications based on the theoretical framework of U&GT and SDT (Klenk et al., 2017). They found out that a combination of fitness applications with social media supports social gratifications (Klenk et al., 2017). "Sharing the results of physical activities via Facebook can provide social support through friends' encouraging comments or their own status information, allowing the comparison of one's own results with others'" (Klenk et al., 2017, p. 187). Furthermore, Park et al. (2009) did already research Facebook groups' user's gratifications and found out that all needs, U&GT defines (seeking information, self-presentation, socialization, and entertainment) play an important role (Park et al., 2009).

There is research on activity trackers, also related to motivational aspects, usefulness, ease of use, and gamification (Clawson, Pater, Miller, Mynatt, & Mamykina, 2015; Fritz et al., 2014; Gao et al., 2015; Giddens et al., 2017; Ilhan & Henkel, 2018; Ledger & McCaffrey, 2014; Shin, Cheon, & Jarrahi, 2015). But if one monitors the data of his/her activity tracker itself (e.g. steps, burned calories, heart rates), why does she/he participate in fitness-related Facebook groups? Our research idea includes four dimensions (D1–D4) (Figure 5.2). The first dimension shows our target group, here, users of activity trackers. Based on the theory of SDT individuals are doing something out of intrinsic or extrinsic motivation (D2). *Something* is in this study defined as using Facebook related to activity tracker- or fitness-related groups (D3). To understand the needs of individuals who joins and uses those Facebook groups we applied U&GT and its four categories (D4).

Based on our research model (Figure 5.2), the study is going to answer the following research questions (RQs):

RQ1: Which gratifications are sought and which are obtained?
RQ2: Is there a correlation between sought and obtained gratifications?
RQ3: Are users more intrinsically or more extrinsically motivated?
RQ4: Do sought gratifications cohere with extrinsic or intrinsic motivation?

RQ5: Do obtained gratifications support the use of activity trackers?

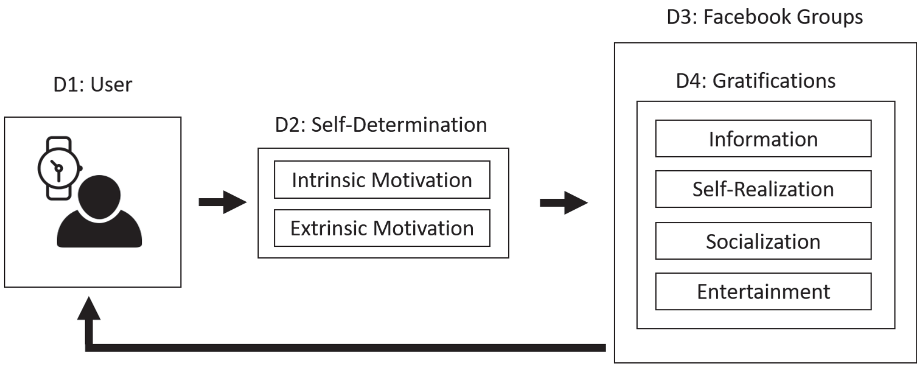

Figure 5.2: Research model.

5.3 Methods

This section describes the investigation's study design. It consists of the collection of quantitative data as outcomes of an online survey and the analysis of the quantitative data in order to answer the five research questions.

An online survey, with the help of eSurvey Creator[1], was created with all in all 26 items. Some of those scale items could not adopt from previous studies as they do not apply U&GT and SDT to comprehend the general use of Facebook groups around health, fitness, activity trackers, weight loss, nutrition and similar topics. The items are formulated by having regard to the core characteristics of the mentioned two theories. Our online survey was divided into three sections. The first section covers demographic information (gender, age, country), activity tracker related information ('Do you have an activity tracker?', 'I have been using an activity tracker since: ...' and 'Without the Facebook group I would stop to use my activity tracker'), the type of user (producer, consumer, participant), testing item ('I'm currently a member of the following Facebook group: Name/Link') and a general free field for further comments. If participants answered the testing item with 'no' the survey was finished. The testing item was necessary to confirm that the participants are really a member of those Facebook groups.

The second section (see Appendix (Table 5.8)) examines the needs why users of Facebook groups use those activity- or fitness-related groups based on the U&GT. The theoretical framework considers both, gratifications sought and gratifications obtained. Participants having an activity tracker got the items (see Appendix (Table 5.8: #9–12)), too. All items of the second section are equipped with a seven-point Likert scale, from 1 'It is absolutely not true', to 7 'It is absolutely true'. Participants got the possibility to choose "No Answer", too. The motives of the U&GT are completed by examples for the participants to support the easier understanding of each motive. The third section (see Appendix (Table 5.9)) deals with the SDT. Besides the intrinsic motivation (Appendix: (Table 5.9 #1)), this section includes ex-

[1]https://www.esurveycreator.com.

trinsic motivation items (Appendix (Table 5.9: #2–5)) as well. The third section is equipped with the same seven-point Likert scale and the category "No Answer," too.

Before distributing the questionnaire, a pretest with five test persons was conducted to clarify discrepancies and vague descriptions. For German Facebook groups, the questionnaire was translated into German otherwise the questionnaire was in English.

The target group for this investigation is restricted. Only Facebook users who joined and use Facebook groups related to investigation's constrained topics come into consideration. Therefore, for each of the 20 analyzed Facebook groups the survey was duplicated with the only adaption of the testing question. Facebook groups such as 'Fitbit Charge 2 Group', 'Garmin vivosmart hr', 'Apple Watch', 'Freeletics Cologne', 'Fitbit For Women', 'Fitbit Weight Watchers Addict', 'Women-Fitness and Nutrition'[2] are examples where the survey was distributed. If one looks to some description of those Facebook groups one can find statements such as "let's post our accomplishments and met other fitbit users and change FITBIT ID'S. Let's form friendships [...] and motivate each other to move!!!", "Feel free to share recipes, ideas, photos of your walks, celebrate stepping milestones or whatever else you want to discuss with the group [...]", "This group is for women [...] here you can ask questions, post recipes, fitness successes, and so on", "A group to discuss the Apple 1, 2 and 3 Series Watches! Post your questions, comments and pictures here!". The frequency of members varies from around 300 to 34,000 members (Ø $\sim$ 5,300). On Facebook there are much more activity tracker- and fitness-related groups but only those are considered if their admins approved the distribution. A lot of Facebook groups did not allow the distribution of the questionnaire. There was no compensation for participants.

All in all, after data preparation 445 of 452 questionnaires, where participants affirmed the use of those groups, the using of activity trackers and completing the survey, are evaluable. The demographic data of our participants is shown in (Table 5.2). As the data are not normally distributed, we worked with the Spearman-Rho correlation for identifying interrelationships between variables. The interpretation of the effect sizes are based on (Cohen, 1988).

Table 5.2: Demographics of respondents.

Item	Answer	Frequency	Percent
Gender	Male	67	15%
	Female	375	84%
	I prefer not say	3	1%
Age	Silent Generation (1925–1945)	2	1%
	Baby Boomers (1946–1960)	26	6%
	Generation X (1961–1980)	184	41%
	Generation Y (1981–1998)	227	51%
	Generation Z (>1998)	6	1%

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[2]Translated from German: Frauen-Fitness und Ernährung

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Item	Answer	Frequency	Percent
Country	Europe	368	84%
	North America	63	14%
	South America	1	0%
	Asia	7	2%
	Australia	6	1%
Operating time	N.A.	3	1%
	<2013	22	5%
	2014	30	7%
	2015	66	15%
	2016	105	24%
	2017	185	42%
	2018	34	8%
Without the group I would stop to use my activity tracker	Yes	3	1%
	No	442	99%

5.4 Results

5.4.1 Gratifications Obtained and Sought Within Activity Tracker- and Fitness-Related Facebook Groups (RQ1)

Based on the description of some Facebook groups, participants have the possibility not only to search for information on activity tracker products, wristbands, exercises and recipes, they are also able to post images of weight loss before and after a diet, to post achievements, to search for friends and to be motivated through other users. Which of those aspects are the most preferred seeking ones? To determine the most sought and obtained motive we calculated statistical values such as median, mean and the standard deviation (the last two values only for additional information as the data is not normally distributed) Table 5.3. The key motive why participants are using those Facebook groups is explained by the motive *Information* (Median: 6). At least half of our participants confirm that it is true that they use this group to receive information. The possibility to realize oneself is the less preferred reason why users are using those groups (Median: 3). Participants reveal that it is not true that they are looking for the possibility to realize themselves. The receiving of achievements, to recognize one's successes (weight loss, stepping milestones) is one aspect, the need to sharing those successes with other, another. The participants do not deny that they occasionally use (Median: 4) those groups out of the fact that they seeking entertainment and socialization. Individuals who are searching for information can assume, based on the results, that they will receive needed information. They confirm that it is true that the use of the Facebook groups enables them to receive information (Median: 6). Conspicuously, while participants do not prospect the possibility to realize themselves more than half of participants state that they nevertheless posted successes occasionally (Median: 4). The Facebook groups try to be in general an informative platform, where users can satisfy their information needs related to activity tracker- or fitness-related topics. Participants agree (Median: 5) that it is rarely true that the use of those Facebook groups enables to feel entertained and to have fun. All in all, comparing the median values between gratifications sought and obtained, in two cases the experience (obtaining a gratification) is higher than the expectation (seeking a gratification), namely for self-presentation and for entertainment. Users do not explicitly seek for self-presentation and for entertainment; however, they get it.

Table 5.3: Gratifications sought and obtained within activity tracker- and fitness-related Facebook groups.

Gratifications	Statistical Values	
	Sought	Obtained
Information	Median = 6 (IQR = 2) Mean = 5.86 (±1.38) N = 436	Median = 6 (IQR = 2) Mean = 5.62 (±1.44) N = 436
Self-Presentation	Median = 3 (IQR = 4) Mean = 3.17 (±1.98) N = 371	Median = 4 (IQR = 3) Mean = 3.69 (±2.09) N = 371
Socialization	Median = 4 (IQR = 4) Mean = 4.11 (±2.01) N = 399	Median = 4 (IQR = 3) Mean = 4.28 (±2.00) N = 399
Entertainment	Median = 4 (IQR = 3) Mean = 4.39 (±1.71) N = 418	Median = 5 (IQR = 2) Mean = 4.65 (±1.69) N = 418

Scale: 1 (It is absolutely not true) – 7 (It is absolutely true); ± (Standard Deviation); IQR (Interquartile Range).

5.4.2 Correlations Between Sought and Obtained Gratifications (RQ2)

Are there correlations between gratifications sought and obtained? Here, the correlations have to be interpreted always bidirectional. Table 5.4 shows the significance levels as well as the effect size. The effect size r = .10 is characterized as low, r = .30 as medium and r = .50 as strong. Based on the results there are nearly in all cases significant correlations between gratifications sought and obtained.

Participants obtained the gratification they sought (and – of course – vice versa). When a user seeks for information, she/he obtains information (.669***); looking for self-presentation, the participant gets it (.649***); hoping of socialization, it indeed happens (.686***); and finally, seeking entertainment is correlated with obtaining entertainment (.698***). All are strong and statistically highly significant correlations. The seeking for a certain gratification results in many cases in obtaining different additional gratifications as well. Seeking for information correlates lowly with entertainment, but not with self-presentation and socialization. Seeking for self-presentation correlates with socialization with a medium effect and with entertainment (however, only on a low level). Looking for socialization, it correlates with all other gratifications obtained, namely information (low effect size), entertainment (medium effect size) and self-presentation (medium effect size). If one seeks for entertainment, she/he obtains except of entertainment itself information (low effect size), self-presentation (low effect size) and socialization (medium effect size).

Table 5.4: Bivariate rank correlation (Spearman's rho) between gratifications sought and obtained.

		Gratifications Obtained			
		Information	Self-Presentation	Socialization	Entertainment
Gratifications Sought	Information	.669*** (N = 436)	.050 (N = 370)	.099 (N = 395)	.179*** (N = 414)
	Self-Presentation	.035 (N = 432)	.649*** (N = 371)	.359*** (N = 394)	.165*** (N = 412)
	Socialization	.189*** (N = 436)	.460*** (N = 374)	.686*** (N = 399)	.328*** (N = 416)
	Entertainment	.216*** (N = 437)	.272*** (N = 374)	.445*** (N = 399)	.698*** (N = 418)

Significance values: * $p < .05$, ** $p < .01$, *** $p < .001$

5.4.3 Users' Intrinsic and Extrinsic Motivations (RQ3)

In fact, participants of activity tracker- or fitness-related Facebook groups are using them based mainly on intrinsic motivation (Median: 6) (Table 5.5). More than half of the participants confirmed that they like it to join those groups and that they do not have any external expectations by joining and doing something within this group. Nobody is compelling the users to join and use those groups (external regulation: Median: 1; introjected regulation: Median: 1).

Two extrinsic motivational factors have some influence, but both are tending to be self-determined. Participants tell that it occasionally happens that they use those groups because they identify with the values and behavior of those groups (identified regulation; Median: 4). Participants confirm that those values are occasionally coherent with the individual's own values and behavior (integrated regulation; Median: 4).

Table 5.5: Use of Facebook groups caused by intrinsic and extrinsic motivation.

Item	Statistical Values
Motives, why I use this Facebook group:	
Intrinsic Motivation	Median = 6 (IQR = 3) Mean = 5.31 ($\pm$1.54) N = 439
External Regulation	Median = 1 (IQR = 0) Mean = 1.23 ($\pm$1.05) N = 439
Introjected Regulation	Median = 1 (IQR = 0) Mean = 1.26 ($\pm$1.05) N = 438
Identified Regulation	Median = 4 (IQR = 4) Mean = 3.89 ($\pm$ 2.02) N = 424
Integrated Regulation	Median = 4 (IQR = 3) Mean = 3.54 ($\pm$1.85) N = 383

Scale: 1 (It is absolutely not true) – 7 (It is absolutely true); $\pm$ (Standard Deviation); IQR (Interquartile Range).

5.4.4 Motivational Background of Sought Gratifications (RQ4)

What is the motivational background of sought gratification (Table 5.6)? We would like to know which kind of motivation (intrinsic or extrinsic) is prevalent with the four defined gratification categories (information, self-presentation, socialization, and entertainment). The negative correlation delivers that the interpretation of the correlation of two data is contrary. If people are seeking for information within those Facebook groups, it does not correlate positively with external (-.149**) and introjected regulation (-.137**). If people would be compelled to use those groups or they would have a bad conscience it is not founded by the need to seek information. The more people using those groups, because they are looking for the possibility to receive information the more it is intrinsically (.250***) motivated. Searching for self-presentation does not significantly correlate with the intrinsic motivation, but with extrinsic subtypes (external: .186***; introjected: .233***; identified: .326***; integrated: .319***). If the decision to use a Facebook group is controlled through looking for the possibility to socialize it exists a significant strong correlation between socialization and identified regulation (.476***) as well as with integrated regulation (.435***). The more the intrinsic motivation or the introjected and identified regulations (extrinsic motivation) is predominant the more participants are seeking for entertainment.

Table 5.6: Correlations between intrinsic and extrinsic motivations and sought gratifications.

			Subtypes of Extrinsic Regulation			
		Intrinsic	External	Introjected	Identified	Integrated
Gratifications Sought	Information	.250*** (N = 434)	-.149** (N = 433)	-.137** (N = 432)	.105* (N = 420)	.090 (N = 380)
	Self-Presentation	.032 (N = 430)	.186*** (N = 430)	.233*** (N = 429)	.326*** (N = 418)	.319*** (N = 378)
	Socialization	.123* (N = 434)	.084 (N = 434)	.122* (N = 433)	.476*** (N = 421)	.435*** (N = 381)
	Entertainment	.263*** (N = 433)	.030 (N = 433)	.078 (N = 432)	.303*** (N = 420)	.259*** (N = 381)

Significance values: *$p < .05$, ** $p < .01$, *** $p < .001$

5.4.5 Gratifications Supporting the Use of Activity Tracker (RQ5)

The study shows that participants do not really need the Facebook groups to continue the use of their activity trackers. 99% of our participants mentioned that they would not stop to use the activity tracker without the use of those groups. Based on the possibility to obtain the chance to receive information, to socialize and to be entertained participants agree that it is indifferent that it supports the use of their activity trackers (Median: 4) (Table 5.7). Self-presentation via a Facebook group does not support the use of an activity tracker (Median: 3).

Table 5.7: Gratifications and the use of activity trackers.

Item	Statistical Values
The use of your activity tracker is supported by. . .	
Information	Median = 4 (IQR = 4) Mean = 4.11 (±2.02) N = 427
Self-Presentation	Median = 3 (IQR = 4) Mean = 3.35 (±2.07) N = 368
Sozialisation	Median = 4 (IQR = 3) Mean = 3.78 (±2.06) N = 391
Entertainment	Median = 4 (IQR = 3) Mean = 4.01 (± 1.91) N = 399

Scale: 1 (It is absolutely not true) – 7 (It is absolutely true); ± (Standard Deviation); IQR (Interquartile Range).

5.5 Discussion

The objective of this study was to find out why users of activity trackers are additionally applying activity tracker- or fitness-related Facebook groups. To answer this basic question, the study was based on two approaches: the U&GT and the SDT. A survey, designed following the basic principles of these two theories, was developed and distributed within different Facebook groups. One main point is to work out the sought and obtained gratifications (information, self-presentation, socialization, entertainment) and the satisfaction related to obtained gratifications. The second main point is to comprehend why Facebook users are tending to do something. Are their activities or their needs to look for gratifications caused by intrinsic or extrinsic motivation?

The demographic values show that participants have not had their activity tracker for too long. Half of 445 participants own their activity trackers since 2017. To the starting time of using a new device (here activity trackers), normally, users need information, for example, related to the ease of use and meaning of measured values (active minutes, sleeping phases). The study shows that an exchange of information is ensured. Within those Facebook groups the information need can be satisfied.

Functionalities of an activity tracker such as step milestones, calories burned, active minutes, sleeping phases are working without social support. But, challenges with other users of activity trackers, obviously, assume that users need other users. Individuals are not equal. Some individuals do not need social reinforcement; they are their own support and motivation. However, there are also individuals who need the support, the feedback, the emotional reinforcement to keep motivated. Facebook groups, which include descriptions like "Let's form friendships" focus on those values and are suited for those individuals.

The participants do not have the need to share their successes in Facebook groups. They are not looking for the possibility to realize themselves by posting and sharing achievements, step milestones, and so on. Indeed, it is assumed that the behavior of other users within those Facebook groups (posting of success), the group description, for example, "Feel free to share recipes, ideas, photos of your walks, celebrate stepping milestones" or invocations of admins to share successes are contagious. Likewise, participants are feeling more entertained in those Facebook groups as they expected. To sum up, based on the U&GT the study confirmed that participants are getting exactly or more than expected what they are seeking for in those groups.

Besides the fact, that participants obtained their sought gratifications, the correlations show that looking for the possibility to satisfy ones' need, for example, receiving information, enables also to feel entertained. Participants who are using those groups for seeking self-presentation obtained the chance to socialize, too. This is accounted by the fact that sharing or posting successes is an activity itself. But, the support through positive feedback and emotional support or compliments does not work without other users. The possibility to get to know other users, to feel motivated through the general social reinforcement can reduce participants fears to feel ashamed and strengthens the user's self-confidence. Generally, the analysis of evaluated data states that not always the sought gratification enables the obtaining of other gratifications and vice versa. Participants who look for self-presentation do not obtain information.

Those Facebook groups are not necessary for the continued use of activity trackers. 99% of participants argue that they would not stop to use their activity tracker without those groups. Considered the fact that an activity tracker is a device that enables the self-quantification by showing up the measured aspects, there is no Facebook group needed to get to know how many steps a user did. But, it is recognizable that the possibility to receive information, to socialize and to feel entertained sometimes support the use of the activity tracker. If someone would like to know how he or she can track an exercise the Facebook group can provide an answer and therefore support the use of the activity tracker. Individuals' social environment does not necessarily have an activity tracker. But without other users there is no possibility to start challenges. Mentioned Facebook groups enable to find other friends or, here, competitors for challenges; this supports the continued use of the activity trackers furthermore. Besides receiving information, feeling entertained and to socialize, self-presentation within those groups is rarely a factor that leads to the support of using activity trackers.

To sum up, the continued use of an activity tracker itself is depending on its own functionalities. Other studies show that the impact and ease of use of activity trackers have an influence on the use as well. However, sometimes the support of the Facebook groups in different ways should be considered as supporting aspect, too, but not as a necessary aspect.

Individuals are doing activities or decisions out of intrinsic or extrinsic motivation. Participants of this study provide the fact that seeking information within those groups is caused through one's own intrinsic motivation without any extrinsic influences. Here, the need to seek information is not induced by external or introjected regulation. Descriptions of Facebook groups "Post and share your experiences, recipes, pictures and so on" encourage users of the group to post something. Self-presentation is caused through subtypes of the extrinsic regulation. Users who share their successes out of identified regulations agree with the values of the group, here to support each other, to share successes and to motivate other persons. Participants who are looking for socialization identify with the rules of the groups. It is important to support other users, to exchange experiences, to meet new users and to give feedback. Participants are not compelled to meet other people or to support each other. The more participants are seeking for entertainment the more this need is caused by their own motivation and the activity itself (to have fun). Beyond that, to seek for entertainment can be caused by identified and integrated regulation (extrinsic motivation) as well. The feeling of being entertained is triggered regularly through different conditions, for example, other users who try to create a funny atmosphere while sharing and chatting with other users. Especially admins try to convey a space of respect but with facility and humor. Based on the evaluated data, it is not possible to indicate for each sought gratification a type of motivation. Instead it is either intrinsic as extrinsic, too.

Ultimately, both theories U&GT and SDT enable an answer and an understanding of gratifications and motivations why some people are using activity tracker- and fitness-related Facebook groups. The understanding of the chosen shared successes or the kind of postings assume a deeper study with, for example, a content analysis. Which kind of successes users are posting?

Health metrics such as calories burned, step milestones, average heart rates, etc. or pictures before and after a diet?

This study has some weak points. Over the entire analysis it should be at the back of one's mind that the groups are not consistent over all. The criteria which Facebook group could be used in this study was depended on the permission of admins and the topic. However, for a first comprehensive analysis of the role of those Facebook groups beside the devices themselves the study enables significant insights.

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Appendix1

Table 5.8: Questions Concerning Uses and Gratifications Theory

#		Item
	U&GT: Sought Gratifications	I use this Facebook group, because I'm looking for the possibility . . .
1		. . . to receive information
2		. . . to realize myself (e.g., to show my success, aims and obtained achievements)
3		. . . to socialize (e.g., for being motivated, for challenges, and emotional reinforcement)
4		. . . to be entertained (e.g., to have fun)
	U&GT: Obtained Gratifications	The use of the Facebook group actually enables me . . .
5		. . . to receive information
6		. . . to realize myself (e.g., to show my success, aims and obtained achievements)
7		. . . to socialize (e.g., for being motivated, for challenges, and emotional reinforcement)
8		. . . to be entertained (e.g., to have fun)
	Support of Activity Tracker	The use of your activity tracker is supported by . . .
9		. . . receiving information within this Facebook group
10		. . . self-realization (e.g., to show my success, aims and obtained achievements) within this Facebook group
11		. . . socialization (e.g., for being motivated, for challenges, and emotional reinforcement) within this Facebook group
12		. . . entertainment (e.g., to have fun) within this Facebook group

Appendix2

Table 5.9: Questions Concerning Self-Determination Theory

#		Item
		Motives, why I use Facebook groups:
1	Intrinsic Motivation	I like to use Facebook groups like this one. I don't have any external expectations.
2	Extrinsic Motivation: External Regulation	I was required (compelled) to use this group. I had no choice.
3	Extrinsic Motivation: Introjected Regulation	I use this group, because otherwise I would have a bad conscience as my circle of friends and acquaintances use groups like this one.
4	Extrinsic Motivation: Identified Regulation	I identify with the aims and behavior of this group and adapt them (e.g., the support of others). I'm agreeing with these practices and values.
5	Extrinsic Motivation: Integrated Regulation	The values and practices of the group are coherent with my own values and practices. I completely adapt them.

6 Users of Fitbit Facebook Groups: A Gender- and Generation-Determined Investigation of Their Motivation and Need

Ilhan, A. (2020). Users of Fitbit Facebook groups: a gender- and generation-determined investigation of their motivation and need. In G. Meiselwitz (Ed.), *Social Computing and Social Media. Design, Ethics, User Behavior, and Social Network Analysis. HCII 2020, (Lecture Notes in Computer Science* (Vol. 12193, pp. 513–533). Springer. doi: https://doi.org/10.1007/978-3-030-49570-1_36

Abstract *This investigation focused on gender-and generation-determined differences regarding the need and use of Fitbit Facebook groups and the motivation to join these groups. Therefore, we applied the Uses and Gratifications Theory (U&GT) and Self-Determination Theory (SDT). This investigation aims to better understand the needs of activity tracking technology users who joined these groups. For this aim, we used an online survey. All in all, 268 participants are analyzed in this investigation. Results reveal that there are only a few gender- and generation-determined differences. This investigation draws on previous studies and allows to expand further research and to stress factors that needed to be considered.*

6.1 Introduction

The importance of healthy living is a lifetime challenge. Being physically active can secure well-being, improve quality of life, and reduce the sedentary lifestyle. According to World Health Organization (2020), "the failure to enjoy adequate levels of physical activity increases the risk of cancer, heart disease, stroke, and diabetes by 20–30% and shortens lifespan by 3–5 years." For a few years, companies such as Fitbit, Samsung, Garmin, and Huawei regularly present new models of activity tracking technologies. These technologies enable users to easily monitor, analyze, and to use health-metrics such as steps, heart rate, burned calories, and sleep quality. According to Liu (Oct. 17, 2019), 30% of US citizens already use wristbands to track activities. These wristbands try to support users to be physically more active through setting step-goals, receiving reminders, or gamification elements (i.e., step challenges, achievements). Not only the promises activity tracking technologies (ATTs) reveal, but the increasing adaption and interest of these technologies might show the capability of these technologies. Studies already investigated the acceptance and usefulness of ATTs (i.e., Fritz, Huang, Murphy, & Zimmermann, 2014; Ilhan & Henkel, 2018; Nelson, Verhagen, & Noordzij, 2016; Shin et al., 2019). The activity tracking technology users surveyed by (Ilhan & Henkel, 2018) agree on the usefulness and the impact of activity trackers.

Besides the possibility to track health and fitness data, the corresponding mobile applications of the activity tracking technologies such as Fitbit include the option of forming and maintaining a community. There, users can share information, post pictures, achievements, or anything else on different topics. The offering of these communities within the application can be supportive of regulating one's objective. Within communities, users can encourage each other or share information and answer questions.

Spaces to seek, produce, and share information online as well as to discuss topics are widespread. From online forums to social networking sites (SNSs), there is a great variety. Facebook is one of the most popular SNSs with about 2.45 billion monthly active users (Clement, 2019) and is today a digital space to connect, share information, and to pass the time. Facebook enables to connect with Facebook users who are sharing diverse common interests (e.g., political, housekeeping (e.g., cooking), health, and fitness). Facebook offers more than 10 million Facebook groups (Newberry, 2019). Therefore, it comes as no real surprise that the initial search for Fitbit groups yields many Facebook groups (both private and public). About nine thousand Facebook users joined the private Facebook group *Fitbit Charge 2 Group*[1], about three thousand the private Facebook group *Fitbit UK*[2], and about one thousand the private Facebook group *Fitbit Charge 3 & Ionic Group*[3]. This raises the question why users of activity trackers are joining those online communities, since ATT have all the functionalities to be aware of one's health and fitness and improvement of being physically more active? First insights already showed that the primary motivation to use fitness and health-related Facebook groups is to seek for information (Ilhan, 2018).

Indeed, Facebook can be a source for getting health-related information. The study of Sharon, Yom-Tov, and Baram-Tsabari (2020) showed that users of a Facebook group *Talking about Vaccines* are seeking information on this topic as well. At least the quality and usefulness of the received information are still individually evaluated and perceived. Regarding the thematic priority, Facebook groups are of interest to users with a common interest and need to be connected (Athanasopoulou & Sakellari, 2015). Even if Athanasopoulou and Sakellari (2015) concentrated on Facebook groups thematizing schizophrenia, findings such as creating awareness, supporting users with this disorder could be general characteristics of health- and fitness-related Facebook groups. Similar characteristics could be stressed out in the study of (Greene, Choudhry, Kilabuk, & Shrank, 2011). Users of the investigated Facebook group shared clinical information, were seeking for guidance and feedback, and emotional support (Sharon et al., 2020). A broad thematic view showed that within Facebook groups, specific health information and experiences are shared and sought. Even though such Facebook groups seem to occupy an important role, the study of Ilhan (2018) highlights that users who are using fitness- and health-related Facebook groups would use their activity trackers also without using the groups. The use of this kind of Facebook groups is crystallized as a supportive opportunity to meet needs but not necessarily to continue the use of activity trackers (Ilhan, 2018).

To the best of our knowledge, there are several studies on Facebook groups regarding health-

[1] https://www.facebook.com/groups/1322932601106678/
[2] https://www.facebook.com/groups/663824983756452/
[3] https://www.facebook.com/groups/fitbitstar

related topics (i.e., Athanasopoulou & Sakellari, 2015; Greene et al., 2011; Sharon et al., 2020), but the research on activity tracker-related groups Ilhan (2018) is still limited. Therefore, to expand the research and to better understand the benefits of these groups as perceived by the users, the following investigation analyses motivations to join Fitbit-related Facebook groups by applying two theories that have the potential to complement each other. Firstly, we applied the Uses and Gratifications Theory (U&GT). The theory claims that people are using a specific media source out of specific needs (e.g., seek for information). The U&GT is an adequate approach to better understand the need for why users choose a particular media, but it is not telling which motivation underlies to join these groups. Therefore, secondly, we made use of the Self-Determination Theory (SDT) to understand not only the need of users but also their motivation to join these Fitbit-related Facebook groups as well. The core of the SDT is defined by different motivational driving forces (extrinsic and intrinsic), which leads people to do activities or decisions.

This investigation is a follow-up study and makes use of the collected data by (Ilhan, 2018). In association with ATT, this study concentrates on Fitbit-related Facebook groups. This investigation should create an added value in many ways. Firstly, it will offer insights if there are gender- and generation-determined differences regarding the need to use Fitbit-related Facebook groups. For this purpose, we apply the U&GT. Secondly, to complete the reasons why users are using these groups, we applied the SDT to allow insights if there are gender- and generation-determined differences as well.

First of all, the theoretical background will show related literature, as well as the applied theories U&GT and SDT followed by the research questions. Subsequently, the used methodology (online survey) and the preparation and applied statistical methods to answer the research questions are presented. The results will be reasonably processed to answer the research questions adequately. In the end, the results will be discussed in order to develop implications.

6.2 Theoretical Background

In this section, we introduce the core of the used theories for this investigation and related literature regarding gender- and generation-determined differences.

The **Uses and Gratifications Theory** enables an audience-centered investigation. This approach leads to understanding why users decided to use specific media concerning the needs they desire to satisfy. U&GT traces back to the time of traditional media channels, where the chosen media enables the seeking of different gratifications (Katz, Blumler, & Gurevitch, 1973-1974, 1974). Part of the U&GT is not only users' seeking behavior for gratifications but also the obtaining of them (Greenberg, 1974; Katz, Haas, & Gurevitch, 1973; Palmgreen, Wenner, & Rayburn, 1980). However, sought and obtained gratifications do not need to accord with each other (Palmgreen et al., 1980).

Today, the approach is used in different contexts, such as ATTs in general (Schaffarczyk & Ilhan, 2019), ATTs with regard to social media or mobile applications (Ilhan, 2018; Klenk, Reifegerste, & Renatus, 2017), and diverse social media platforms (Joinson, 2008; Raacke & Bonds-Raacke, 2008; Scheibe, Göretz, Meschede, & Stock, 2018; Scheibe & Zimmer, 2019; Tanta, Mihovilovic, & Sablic, 2014; Whiting & Williams, 2013; Zimmer & Scheibe, 2019; Zimmer, Scheibe, & Stock, 2018). There are different types of gratifications detected and investigated. Four common gratifications, based on (McQuail, 1983) are *information, self-presentation, socialization, and entertainment*. According to these four gratifications, the study by Park, Kee, and Valenzuela (2009) confirmed that they were sought while participating in Facebook groups as well. According to Ilhan (2018), ATT users mainly look for the possibility to receive information within fitness- and health-related Facebook groups. Nevertheless, apart from these four gratifications, (Whiting & Williams, 2013, p. 362) identified ten motives "social interaction, information seeking, pass time, entertainment, [...]" as well. According to Tanta et al. (2014), the surveyed participants use Facebook, among others, for socializing and communicating with their friends and obtaining information about social events. In the end, gratifications needed to be adapted and modified related to their context and the investigated aim. Now, as we already know that there are several studies on the U&GT and social media, what about gender-determined differences? Is there any evidence that the sought and obtained gratifications differentiate regarding gender, especially in the context of physical activity and ATTs?

According to Krasnova, Veltri, Eling, and Buxmann (2017), gender-specific differences are apparent. While women of their study tend more to use SNSs regarding socializing aspects and getting social information, men tend to use SNSs to seek general information (Krasnova et al., 2017). By applying the U&GT, Klenk et al. (2017) investigated the gender-determined information sharing behavior of physical activity within mobile applications, and Facebook. Furthermore, they found out that men tend to share their results with others (achieved with the Runtastic mobile application) more often than women in Facebook groups. Interestingly, from the surveyed Runtastic users, 84.7% joined Facebook groups related to fitness-related Facebook groups (e.g., Runtastic) (Klenk et al., 2017).

Apart from gender-determined differences, we are focusing on generation-determined differences as well. According to Fietkiewicz, Lins, Baran, and Stock (2016), different generations use social media platforms differently. Besides gender-specific differences, Klenk et al. (2017) investigated generation-determined differences as well. Older participants are willingly sharing more results in the fitness app Runtastic than younger participants (Klenk et al., 2017). For getting a comprehensive insight, it is necessary to expand the gender- and generation-determined investigations in this research area. While it is confirmed that some frequent gratifications appear (i.e., information, social aspects), it still remains uncertain if they might be affected by aspects such as gender and age. Especially since the "Facebook usage is significantly different between gender, with 63% of men using the site compared to 75% of women [...]" and "it wide disparity among age groups" (Newberry, 2019). Therefore, based on the U&GT and the rarely available investigations, we formulate the following research questions (RQ):

RQ1: To what extent do male and female activity tracker users differ regarding their sought and obtained gratifications within the Fitbit Facebook groups?

RQ2: To what extent do the generations differ regarding the sought and obtained gratification within the Fitbit Facebook groups?

The **Self-Determination Theory** states that motivation is not simply dichotomous (intrinsic or extrinsic) (Deci & Ryan, 1985, 2000). Extrinsic motivation is defined based on the source and to what extent it is self-determined. Activities and decisions are distinguishable regarding their external and internal nature. The more external circumstances influence actions, the less self-determined people are (Ryan & Deci, 2000). According to Ryan and Deci (2000); Ryan, Williams, Patrick, and Deci (2009), extrinsic motivation can be divided into four subcategories regarding their regulation nature *external regulation, introjected regulation, identified regulation, and integrated regulation*. The external regulation is the lowest of all self-determined motivational actions. Someone is extrinsically motivated if s/he is doing something only to avoid punishments or to get rewards. These actions are leading back to external regulations. More self-determined actions within the extrinsic motivation are characterized through the identified and integrated regulation. Even though people identify external values with their values and recognize them as harmonious, it is not the activity itself that is perceived enjoyable and leads to specific actions. This leads to intrinsic motivation. People are intrinsically motivated when they perceive the activities themselves enjoyable and exciting. Here, the activity itself is at the forefront. Actions based on intrinsic motivation are the strongest self-determined ones (Ryan & Deci, 2000; Ryan et al., 2009). In the end, people are also able to do something without any reason or intention. According to Ryan and Deci (2000); Ryan et al. (2009), there is the talk of amotivation. Here, the regulation is called impersonal and is motivated by having no intention at all, incompetence, or lack of control (Ryan & Deci, 2000; Ryan et al., 2009).

There are few studies which already investigated users' driving motivational force and willingness to share information about their physical activity on Facebook (Stragier, Evens, & Mechant, 2015) or to join health- and fitness-related Facebook groups (Ilhan, 2018). According to Stragier et al. (2015), the surveyed users of the mobile application Strava are rather intrinsically motivated to share their physical activity status on Facebook. Further, surveyed users by (Ilhan, 2018) joined mostly out of internal reasons, here because they were intrinsically motivated. There are also existing a few studies combining physical activity intervention with the use of Facebook (Wang, Leng, & Kee, 2015). Wang et al. (2015) stresses that more research is needed to understand the effect of Facebook regarding physical activity intervention. They also mention "that the additional use of Facebook may not have increased the level of physical activity participation significantly" (Wang et al., 2015, p. 220). Another study (Divine, Watson, Baker, & Hall, 2019) found out that the use of Facebook can have a positive impact on exercise motivation, even if using Facebook is related to external and introjected regulation. Apart from concentrating on the SDT and Facebook, the study of (Schaffarczyk & Ilhan, 2019) investigated activity tracking technology users' motivation based on the SDT. The participants were both intrinsically and extrinsically (external and integrated regulation) motivated to use the ATTs (Schaffarczyk & Ilhan, 2019). Ferguson, Gutberg, Schattke, Paulin, and Jost (2015) stresses out that it is also crucial to investigate the older populations regarding the SDT and their motivational regulations. Drawn on the studies that already did the first step into understanding the SDT and the use of Facebook, we would like to continue this research field by answering the following two research questions:

RQ3 :To what extent does users' motivation to join Fitbit-related Facebook groups differ based on gender?
RQ4: To what extent does the generations' motivation to join Fitbit-related Facebook groups differ?

6.3 Methods

6.3.1 Online Survey

The online survey was distributed from January 2018 to February 2018 on different health- and fitness-related Facebook groups. The online survey was created with a free online tool[4]. This investigation is using the dataset by (Ilhan, 2018) collected in 2018. As Fitbit is vigorously investigated comparing to the other ATT brands, we decided to restrict the sample. Investigations around Fitbit are mostly focusing on interventions, the accuracy, the feasibility, and the acceptance of them. Therefore, we concentrated only on Fitbit-related Facebook groups, where the survey back then was distributed. The administrators or moderators were asked through a direct Facebook message, if it is allowed to share the survey within the Facebook groups. All in all, the sample of 268 participants is connected to one of eight Fitbit-related Facebook groups selected for this investigation. The survey can be divided into three parts. Firstly (1), the survey contains questions regarding demographics (i.e., gender and age) and general questions to verify that the participants were a member of the surveyed Facebook group. Secondly (2), eight items were assigned to the U&GT to investigate the sought and obtained gratifications. The gratifications investigated for both sought and obtained are *information, self-presentation, socialization, and entertainment* (McQuail, 1983). Sought gratifications were formulated with "I use this Facebook group, because I'm looking for the possibility ..." while obtained gratifications were introduced with the sentence "The use of the Facebook group actually enables me..." Thirdly (3), the last section represents the statements (all in all seven statements) based on the SDT. All statements, according to Theory Sect. (2) and (3), are equipped with a 7-point Likert scale from 1–'Strongly Disagree' to 7–'Strongly Agree.' The survey was available both in German and English and was pretested by five persons.

6.3.2 Data Preparation and Statistical Analysis

The data was prepared and analyzed with the Syntax of IBM SPSS Statistics 26. The answer possibility *I don't know* was coded as missing value; otherwise, statistical calculations are getting falsified. The data compiled through the Likert scale were handled as ordinal-scaled as some of the variables were not normally distributed. This was tested with the Shapiro-Wilk test. Because we handled our data as ordinally scaled, we used two nonparametric tests to investigate differences regarding the distributions.

[4]https://www.esurveycreator.com

To investigate if there are gender-determined differences (RQ1 & RQ3), we used the Mann-Whitney U test by using the new dialog fields instead of the legacy dialogs. The Mann-Whitney U test is a nonparametric rank-based test based on two groups on an independent variable, here gender (female, male) and a dependent ordinal-scaled variable such as statements with a Likert scale (Laerd Statistics, 2018b). To investigate generation-determined differ- ences (RQ2 & RQ4), we used the Kruskal-Wallis H test (new dialog fields within SPSS), because we have more than two groups of generations (Laerd Statistics, 2018a). To determine generation-determined differences, the grouping of participants' age, based on (Fietkiewicz et al., 2016) *(Silver Surfers (older than 59 years old), Generation X (between 40 and 59 years old), Generation Y (between 24 and 39 years old), Generation Z (younger than 24 years old)*, was needed.

6.4 Results

6.4.1 Gender-Determined Differences Regarding Their Sought and Obtained Gratifications Within the Fitbit Facebook Groups (RQ1)

Table 6.1 shows that there are no gender-determined differences regarding the distribution of the sought gratifications. Female and male participants are looking mainly for the possibility to receive information (Median equals 6 *(Agree)*) and are not looking for self-presentation (Median equals 2 *(Disagree)*). Further, regarding the sought gratification *socialization*, the Interquartile Range (IQR) for the female participants is higher than for the male participants. This indicates that even if the median equals 4 *(Neither Agree nor Disagree)*, female participants' answers are strongly scattered around this value.

Table 6.1: Gender-determined differences regarding sought gratifications, N = 267. Abbrev. Mean Rank (MR), Median (Mdn), Interquartile Range (IQR), Mann-Whitney U Test (U Test), $p < .05$*, $p < .01$**, $p < .001$***.

Sought gratifications			Descriptive statistics			Rank-based nonparametric test
	Gender	N	MR	Mdn	IQR	U test
Information	Male	25	130.96	6	2	$U = 2949.000$, $z = -.112$, $p > .05$
	Female	239	132.66	6	2	
Self-presentation	Male	25	132.32	2	3.5	$U = 2983.000$, $z = .131$, $p > .05$
	Female	235	130.31	2	3	
Socialization	Male	25	142.06	4	2	$U = 3226.500$, $z = .703$, $p > .05$
	Female	238	130.94	4	4	
Entertainment	Male	25	142.82	4	2	$U = 3245.500$, $z = .797$, $p > .05$
	Female	237	130.31	4	2	

According to (Appendix 1), the aggregated values of participants who disagree that they are looking for the possibility to socialize (Likert values (1)–(3)) are about 45% out of 238 female participants. The median for female and male participants regarding sought gratification *en-*

tertainment equals 4. Nevertheless, if we add the values from (1) to (3) (see Appendix 1) for the sought gratification *entertainment*, the results show that female and male participants agree on any level that they are seeking for the possibility to be entertained within the Fitbit groups.

According to Table 6.2, this investigation shows no significant gender-determined differences regarding the distribution of the obtained gratifications, even if there are few differences recognizable. Female participants (81.6% out of 239 female participants) and male participants (72% out of 25 male participants) agree that using the Fitbit Facebook group enables them to receive information (see Appendix 2). As for male participants, the median for obtained gratification *self-presentation* equals 3 *(Somewhat Disagree)*, and for female participants, the median equals 4 *(Neither Agree nor Disagree)*.

According to the general distribution and the aggregating of values (see Appendix 2), female participants equally tend to disagree more (46.7% out of 201 female participants) and to agree a little less (42.3% out of 201 female participants). The answers of male participants are distributed differently since there are 56% out of 25 male participants fully disagreeing (aggregating all levels of disagreement).

Table 6.2: Gender-determined differences regarding obtained gratifications, $N = 267$. Abbrev. Mean Rank (MR), Median (Mdn), Interquartile Range (IQR), Mann-Whitney U Test (U Test), $p<.05$*, $p < .01$**, $p < .001$***.

Obtained gratifications			Descriptive statistics			Rank-based nonparametric test
	Gender	N	MR	Mdn	IQR	U test
Information	Male	25	121.20	6	3	U = 2705.000, z = -.810, p > .05
	Female	239	133.68	6	2	
Self-presentation	Male	25	99.90	3	2.5	U = 2172.500, z = -1.116, p > .05
	Female	201	115.19	4	3.5	
Socialization	Male	25	117.86	5	2.5	U = 2621.500 z = -.128, p > .05
	Female	213	119.69	4	3	
Entertainment	Male	25	113.02	4	2	U = 2500.500, z = -.989, p > .05
	Female	227	127.98	5	3	

6.4.2 Generation-Determined Differences Regarding Their Sought and Obtained Gratifications Within the Fitbit Facebook Groups (RQ2)

According to Table 6.3, the Kruskal-Wallis H test reports that agreeing on seeking for information (reason to join Fitbit Facebook groups) significantly differed between generations, $H(3) = 8.555$, $p = .036$. Considering the sought gratifications of *self -presentation, socialization, and entertainment*, there are no significant generation-determined differences detected. Even though Silver Surfers tend to agree (Median equals 5 *(Somewhat Agree))* more than the other generations that they are using the Fitbit Facebook groups because they are looking for the possibility to socialize (i.e., being motivated for challenges, and emotional reinforcement). As the participants already use the Fitbit Facebook groups, the question arises whether there are existing generation-determined differences regarding the obtained gratifications. According to Table 6.4, the Kruskal-Wallis H test reports that agreeing on obtaining information (during the use of Fitbit Facebook groups) significantly differed between generations, $H(3) = 9.390$, $p = .025$.

Table 6.3: Generation-determined differences regarding sought gratifications, N = 268. Abbrev. Generation (Gen.), Silver Surfers (SS), Generation X (GX), Generation Y (GY), Generation Z (GZ), Mean Rank (MR), Median (Mdn), Interquartile Range (IQR), Kruskal-Wallis H Test (H Test), $p < .05^*$, $p < .01^{**}$, $p < .001^{***}$.

Sought gratifications			Descriptive statistics			Rank-based nonparametric test
	Gen.	N	MR	Mdn	IQR	H test
Information	SS	12	158.17	7	1.75	$H(3) = 8.555$, $p = .036^*$
	GX	105	143.78	7	2	
	GY	130	125.04	6	2	
	GZ	17	101.74	6	1.5	
Self-presentation	SS	12	163.21	4	5.75	$H(3) = 3.008$, $p > .05$
	GX	101	125.48	2	3	
	GY	131	132.86	2	3	
	GZ	17	126.76	2	3	
Socialization	SS	12	152.08	5	4.75	$H(3) = 3.616$, $p > .05$
	GX	104	140.24	4	4	
	GY	131	126.95	4	3	
	GZ	17	114.09	3	3	
Entertainment	SS	12	135.17	4	3.75	$H(3) = .681$, $p > .05$
	GX	103	135.08	4	3	
	GY	131	130.89	4	2	
	GZ	17	119.71	4	3.5	

Table 6.4: Generation-determined differences regarding obtained gratifications, N = 268. Abbrev. Generation (Gen.), Silver Surfers (SS), Generation X (GX), Generation Y (GY), Generation Z (GZ), Mean Rank (MR), Median (Mdn), Interquartile Range (IQR), Kruskal-Wallis H Test (H Test), $p < .05^*$, $p < .01^{**}$, $p < .001^{***}$.

Obtained gratifications			Descriptive statistics			Rank-based nonparametric test
	Gen.	N	MR	Mdn	IQR	H test
Information	SS	12	155.42	6.5	2	$H(3) = 9.390$, $p = .025^*$
	GX	105	144.83	6	2	
	GY	131	119.19	5	3	
	GZ	17	150.50	6	2	
Self-presentation	SS	11	120.14	5	5	$H(3) = 1.314$, $p > .05$
	GX	88	116.43	4	4	
	GY	113	109.77	3	3	
	GZ	15	127.10	5	4	
Socialization	SS	11	126.32	4	3	$H(3) = .676$, $p > .05$
	GX	91	123.85	5	3	
	GY	121	116.67	4	3	
	GZ	16	118.94	5	3.75	
Entertainment	SS	12	123.79	4.5	2.5	$H(3) = 1.503$, $p > .05$
	GX	98	133.97	5	3	
	GY	127	122.55	4	3	
	GZ	16	122.03	4.5	3	

6.4.3 Gender-Determined Motivation to Join Fitbit-Related Facebook Groups (RQ3)

The need why users decided to use Fitbit Facebook groups enables the first insight, but what about the motivation, which leads to the decision to join these groups. All in all, Table 6.5 shows that the Mann-Whitney U test revealed one significant difference between female (Mean Rank = 131.16) and male participants (Mean Rank = 145.90) regarding the external regulations. Even though the median is equal for both, the mean rank for the male participants is higher. This shows that male participants tend to disagree a little bit less than female participants. According to Table 6.5, both female and male participants mainly agree that they joined the Fitbit Facebook group out of intrinsic motivation. These Fitbit Facebook groups are for both male and female participants not only as pastime, as both are mainly disagreeing that they joined this group because they were bored. Regarding the determined extrinsic regulations, the more self-determined the regulations are (identified and integrated regulation), the more the median value increases.

Table 6.5: Gender-determined differences regarding the motivation, N = 267. Abbrev.Mean Rank (MR), Median (Mdn), Interquartile Range (IQR), Mann-Whitney U Test (U Test), $p < .05^*$, $p < .01^{**}$, $p < .001^{***}$.

Self-determination				Descriptive statistics			Rank-based non-parametric test
Motivation	Regulation	Gender	N	MR	Mdn	IQR	U Test
Extrinsic	External	Male	24	145.90	1	0	U = 3201.500, z = 2.180, p = .029*
		Female	240	131.16	1	0	
	Introjected	Male	24	147.00	1	0	U = 3228.000, z = 1.921, p > .05
		Female	240	131.05	1	0	
	Identified	Male	24	118.90	3	3.75	U = 2553.500, z= -.643, p > .05
		Female	231	128.95	4	3	
	Integrated	Male	23	108.39	4	4	U = 2217.00, z= -.476, p > .05
		Female	205	115.19	4	3	
Intrinsic	Intrinsic	Male	24	113.08	5	3.75	U = 2414.000, z= -1.306, p > .05
		Female	239	133.90	5	3	
Amotivation ("Boredom")	Non-regulation	Male	24	126.88	1	2	U = 2745.000, z = .069, p > .05
		Female	227	125.91	1	2	
Amotivation ("Just for heck of it")	Non-regulation	Male	24	127.71	4	3.5	U = 2765.000, z= -.161, p > .05
		Female	235	130.23	3	4	

6.4.4 Generation-Determined Motivation to Join Fitbit-Related Facebook Groups (RQ4)

When analyzing the generation-determined differences, the Kruskal-Wallis H test reveals only generation-determined differences for the amotivation *Boredom*. According to Table 6, the Kruskal-Wallis H test reports that the amotivation (Boredom) (reason to join Fitbit Facebook groups) significantly differed between generations, H(3) = 10.542, p = .014. The mean rank for Generation Y (139.10) is higher than for Generation Silver Surfer (90.67). Even if both generations still tend to disagree that they joined the Fitbit Facebook groups out of boredom, Generation Y tends a little bit less to disagree overall. Likewise, this is similar to Generation X (Mean Rank = 129.36) and Generation Y (Mean Rank = 139.10). Nevertheless, all four generations mainly agree that they joined the Fitbit Facebook group because it was a self-determined decision and intrinsically regulated (Table 6.6).

Table 6.6: Generation-determined differences regarding the motivation, N = 268. Abbrev. Generation (Gen.), Silver Surfers (SS), Generation X (GX), Generation Y (GY), Generation Z (GZ), Mean Rank (MR), Median (Mdn), Interquartile Range (IQR), Kruskal-Wallis H Test (H Test), $p < .05^*$, $p < .01^{**}$, $p < .001^{***}$.

Self-determination				Descriptive statistics			Rank-based non-parametric test
Motivation	Regulation	Gen.	N	MR	Mdn	IQR	H test
Extrinsic	External	SS	12	135.75	1	0	$H(3) = 1.290$, $p > .05$
		GX	103	132.83	1	0	
		GY	133	133.91	1	0	
		GZ	17	125.00	1	0	
	Introjected	SS	12	120.50	1	0	$H(3) = 1.499$, $p > .05$
		GX	103	132.39	1	0	
		GY	133	134.21	1	0	
		GZ	17	136.03	1	0	
	Identified	SS	12	125.33	4	1.75	$H(3) = 1.560$, $p > .05$
		GX	101	122.21	3	5	
		GY	126	132.21	4	3	
		GZ	17	140.59	4	3.5	
	Integrated	SS	12	124.21	4	2.75	$H(3) = 1.214$, $p > .05$
		GX	93	109.49	3	4	
		GY	109	118.09	4	3	
		GZ	15	119.30	4	2	
Intrinsic	Intrinsic	SS	12	173.63	6	2	$H(3) = 5.059$, $p > .05$
		GX	103	129.36	5	3	
		GY	132	133.77	5	3	
		GZ	17	112.65	5	2	
Amotivation ("Boredom")	Non-regulation	SS	12	90.67	1	0	$H(3) = 10.542$, $p = .014^*$
		GX	100	117.07	1	1	
		GY	123	139.10	2	3	
		GZ	17	116.12	1	1.5	
Amotivation ("Just for heck of it")	Non-regulation	SS	12	120.83	3.5	4	$H(3) = .359$, $p > .05$
		GX	102	129.95	4	5	
		GY	128	131.67	3	4	
		GZ	17	124.21	2	5	

6.5 Discussion

The investigation's aim was the identification of gender- and generation-determined differences regarding the motivation and need to join and use Fitbit Facebook groups. In doing so, the investigation revealed, except for a few significant differences, that both female and male participants and the four investigated generations have similar needs and motivational reasons. For this study, we used a dataset (based on an online survey) that was already collected in 2018.

Answering **RQ1** shows that both female and male participants are mainly looking for the possibility to seek for information. Here, there are no gender-determined differences. All in all, Facebook is recognized as a digital space for exchanging information on different topics. Individuals who joined Facebook and Facebook groups bring along different experiences, and varying amounts of knowledge, which might be enriching. For a better understanding of which kind of information female and male participants are looking for, further studies are needed. According to Tanta et al. (2014), participants obtained information about social events. Here, we do not know exactly what kind of information participants sought and obtained. For this approach, a content analysis of postings could be useful, as the content itself can be characterized. As this study investigated the gratification sought *information* very broadly, a subdivision in different types of information might show gender-determined differences and overall varying distribution regarding the agreement as well. An assumption for non-gender-determined differences could be the fact that the use of Fitbit Facebook groups for information is predefined by the groups itself. Some Facebook groups have descriptions, where the main aim might be the exchange of information. Therefore, users who joined this group might share a common need and interest.

Interestingly, according to Klenk et al. (2017), where men tend to share their results with others more than women in Facebook groups could not be confirmed by this study. On the contrary, both female and male participants mainly disagree (Median equals 2 *(Disagree)*) that they are looking for the possibility to show their success, aims, and obtained achievements. Here the question arises if there are other factors that could affect the need for self-presentation. For example, how long do the participants have their activity tracking device? If they had the wearable for a long-time, the need to share the results might decrease. Further, it also can depend on the reason, why users bought an activity tracking device. In the beginning, users might be enthusiastic and excited, for example, collecting and sharing badges. Further, the behavioral stage might play an important role, as well. For instance, if they are at the beginning of changing their behavior, to be physically more active, sharing their success might be more important than later. According to the obtained gratifications, there are no significant gender-determined differences.

The results for **RQ2** show that there are existing generation-determined differences regarding the sought gratification *information*. Interestingly, even if the sample size for the Silver Surfers is small, the mean rank for sought information is the highest. This could indicate that especially the older participants have an increased need to receive information in a straightforward setting. All they need is a Facebook account and to join a Facebook group. Further, according to Newberry (2019), the elderly population is more and more joining Facebook. Also, if the generation-determined differences regarding socialization are not statically significant, it is still evident that the Silver Surfers tend to somewhat agree that they are seeking for the possibility to get social support such as an invitation for challenges or emotional reinforcement. As the sample size of the Silver Surfers is small, in-depth interviews might be reasonable to understand better why the Silver Surfer somewhat agree that they are looking for this possibility and also if it is easier to get it through the Facebook group. We assume that for the generation Silver Surfers, it might be more challenging to connect with other Fitbit users as compared to younger participants who might be surrounded by more users in their everyday life. Therefore, those Fitbit Facebook groups might be a chance for the Silver Surfers to get social contacts supporting them in being physically more active and motivated. The generalization of this assumption needs further studies. Besides the sought gratifications, are there generation-determined differences regarding the obtained gratifications? There is one significant generation-determined difference in obtaining information. Interestingly, while Silver Surfers mainly somewhat agree that they are using the Fitbit Facebook group to socialize, they also primarily somewhat agree that the Fitbit groups indeed enable it.

RQ1 and RQ2 are focusing on the sought and obtained gratifications, the results of **RQ3** show to what extent the decision to join a Facebook was self-determined, and if there are gender-determined differences. Male and female participants significantly differ regarding external regulation. All in all, female and male participants have mainly joined the Fitbit Facebook group based on intrinsic regulation. Based on the results, we assume to have some bearing on the sought gratification information and the motivational driving forces. We know that the female and male participants sought mainly for information. This indicates they have a specific need and did not join the group because they were bored. Further, it could be assumed that the participants joined other Facebook groups as well and experienced information exchange. This could be a reason why they prefer to join Fitbit Facebook groups to receive information as well.

Last but not least, answering **RQ4** focused on generation-determined differences regarding the SDT. In contrast to the one gender-determined significant difference, here the Kruskal-Wallis H test revealed generation-differences based on the amotivation (Boredom). But, overall, participants did not join Fitbit Facebook groups out of boredom.

6.6 Conclusion

Based on answering the research questions (RQ1–RQ4), what are the take-home messages?

First of all, it should be mentioned that this study has some limitations. As this investigation focused on gender- and generation-determined differences, the sample size for male participants and as well as for Generation Z and Silver Surfer, is rather small. According to Newberry (2019), the elderly population is joining Facebook more and more. Therefore, there is a further study needed. As it is a non-probabilistic distributed survey, the controlling of getting specific participants from each group is not possible, as we do not know how the distribution of the groups looks like. Further, as this study focused only on two aspects (gender and age), other factors might influence the results as well. How long do the participants have and use their wearable? Might this factor influence the need to self-present and socialize? Here it would be adequate to have a sample with newbies as well as users like in this one, who have their wearable up to 1–3 years or more.

According to the U&GT, it could be necessary to sub define gratifications, especially the gratifications *self-presentation* and *socialization*, as they were equipped with a lot of examples. This could help to see which aspects exactly are sought and obtained by the participants. Nevertheless, this investigation shows that there are only a few differences regarding gender- and generation-determined differences. But this might indicate that regarding Fitbit groups, the participants are pursuing similar aims and have the same needs. Especially if one is considering the description of the groups, they already point out what the focus of this group is. For example, there are existing groups only for challenges and motivation and then groups where they exchange information such as technical support.

In the end, the circumstances that the elderly population is joining Facebook more and more Newberry (2019), could be used to integrate them in Fitbit groups and to ask for their (information) need specifically. Even if the study of Ilhan (2018) shows that participants would use their activity tracker also without the groups, these groups might still be supportive to be physically active. Here, it would be necessary to investigate Fitbit groups which are focusing on challenges and motivation.

Summarized, this study indicates that there are only a few gender- or generation-determined differences of questioned aspects (such as sought or obtained gratifications and the motivational source).

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Appendix1

Sought Gratifications		Likert Scale (1-Strongly Disagree – 7-Strongly Agree)							
		N	1	2	3	4	5	6	7
Information	Male	25	1 (4.0%)	1 (4.0%)	1 (4.0%)	1 (4.0%)	3 (12.0%)	8 (32.0%)	10 (40.0%)
				12%		4.0%		**84%**	
	Female	239	3 (1.3%)	3 (1.3%)	14 (5.9%)	21 (8.8%)	45 (18.8%)	44 (18.4%)	109 (45.6%)
				8.5%		8.8%		**82.8%**	
Self-Presentation	Male	25	8 (32.0%)	5 (20.0%)	4 (16.0%)	2 (8.0%)	2 (8.0%)	0 (0.0%)	4 (16.0%)
				68%		8.0%		24%	
	Female	235	80 (34.0%)	40 (17.0%)	32 (13.6%)	31 (13.2%)	16 (6.8%)	17 (7.2%)	19 (8.1%)
				64.6%		13.2%		22.1%	
Socialization	Male	25	2 (8.0%)	2 (8.0%)	4 (16.0%)	7 (28.0%)	5 (20.0%)	2 (8.0%)	3 (12.0%)
				32%		28.0%		**40%**	
	Female	238	44 (18.5%)	30 (12.6%)	33 (13.9%)	35 (14.7%)	32 (13.4%)	30 (12.6%)	34 (14.3%)
				45%		14.7%		40.3%	
Entertainment	Male	25	1 (4.0%)	2 (8.0%)	3 (12.0%)	7 (28.0%)	6 (24.0%)	2 (8.0%)	4 (16.0%)
				24%		28.0%		**48%**	
	Female	237	19 (8.0%)	28 (11.8%)	32 (13.5%)	56 (23.6%)	45 (19.0%)	31 (13.1%)	26 (11.0%)
				33.3%		23.6%		**43.1%**	

Appendix2

Obtained Gratifications		Likert Scale (1-Strongly Disagree – 7-Strongly Agree)							
		N	1	2	3	4	5	6	7
Information	Male	25	1 (4.0%)	2 (8.0%)	2 (8.0%)	2 (8.0%)	4 (16.0%)	6 (24.0%)	8 (32.0%)
				20.0%		8.0%		**72%**	
	Female	239	4 (1.7%)	6 (2.5%)	12 (5.0%)	22 (9.2%)	61 (25.5%)	41 (17.2%)	93 (38.9%)
				9.2%		9.2%		**81.6%**	
Self-Presentation	Male	25	4 (16.0%)	7 (28.0%)	3 (12.0%)	5 (20.0%)	2 (8.0%)	2 (8.0%)	2 (8.0%)
				56%		20.0%		24%	
	Female	201	41 (20.4%)	25 (12.4%)	28 (13.9%)	22 (10.9%)	35 (17.4%)	15 (7.5%)	35 (17.4%)
				46.7%		10.9%		42.3%	
Socialization	Male	25	3 (12.0%)	3 (12.0%)	2 (8.0%)	4 (16.0%)	8 (32.0%)	0 (0.0%)	5 (20.0%)
				32%		16.0%		**52%**	
	Female	213	28 (13.1%)	17 (8.0%)	25 (11.7%)	45 (21.1%)	25 (11.7%)	33 (15.5%)	40 (18.8%)
				32.8%		21.1%		**46%**	
Entertainment	Male	25	2 (8.0%)	1 (4.0%)	4 (16.0%)	7 (28.0%)	7 (28.0%)	2 (8.0%)	2 (8.0%)
				28%		28.0%		**44%**	
	Female	227	14 (6.2%)	20 (8.8%)	26 (11.5%)	50 (22.0%)	45 (19.8%)	30 (13.2%)	42 (18.5%)
				26.5%		22.0%		**51.5%**	

Appendix3

Sought Gratifications		Likert Scale (1-Strongly Disagree – 7-Strongly Agree)							
		N	1	2	3	4	5	6	7
Information	Silver S.	12	0 (0%)	0 (0%)	0 (0%)	2 (16.7%)	1 (8.3%)	1 (8.3%)	8 (66.7%)
				0%		16.7%		**83.3%**	
	Gen. X	105	2 (1.9%)	4 (3.8%)	2 (1.9%)	6 (5.7%)	15 (14.3%)	21 (20.0%)	55 (52.4%)
				7.6%		5.7%		**86.7%**	
	Gen. Y	130	2 (1.5%)	0 (0%)	12 (9.2%)	11 (8.5%)	28 (21.5%)	24 (18.5%)	53 (40.8%)
				10.7%		8.5%		**80.8%**	
	Gen. Z	17	0 (0%)	0 (0%)	1 (5.9%)	3 (17.6%)	4 (23.5%)	6 (35.3%)	3 (17.6%)
				5.9%		17.6%		**76.4%**	
Self-Presentation	Silver S.	12	3 (25.0%)	2 (16.7%)	0 (0%)	2 (16.7%)	0 (0%)	1 (8.3%)	4 (33.3%)
				41.7%		16.7%		**41.6%**	
	Gen. X	101	39 (38.6%)	14 (13.9%)	15 (14.9%)	14 (13.9%)	4 (4.0%)	5 (5.0%)	10 (9.9%)
				67.4%		13.9%		18.9%	
	Gen. Y	131	40 (30.5%)	26 (19.8%)	19 (14.5%)	15 (11.5%)	13 (9.9%)	10 (7.6%)	8 (6.1%)
				64.8%		11.5%		23.6%	
	Gen. Z	17	6 (35.3%)	3 (17.6%)	2 (11.8%)	3 (17.6%)	1 (5.9%)	1 (5.9%)	1 (5.9%)
				64.7%		17.6%		17.7%	
Socialization	Silver S.	12	3 (25.0%)	0 (0%)	0 (0%)	1 (8.3%)	5 (41.7%)	0 (0%)	3 (25.0%)
				25.0%		8.3%		**66.7%**	
	Gen. X	104	19 (18.3%)	8 (7.7%)	15 (14.4%)	13 (12.5%)	16 (15.4%)	15 (14.4%)	18 (17.3%)
				40.4%		12.5%		**47.1%**	
	Gen. Y	131	21 (16.0%)	20 (15.3%)	18 (13.7%)	28 (21.4%)	13 (9.9%)	17 (13.0%)	14 (10.7%)
				45%		21.4%		33.6%	
	Gen. Z	17	3 (17.6%)	4 (23.5%)	4 (23.5%)	0 (0%)	3 (17.6%)	1 (5.9%)	2 (11.8%)
				64.6%		0%		35.3%	
Entertainment	Silver S.	12	2 (16.7%)	1 (8.3%)	1 (8.3%)	3 (25.0%)	0 (0%)	3 (25.0%)	2 (16.7%)
				33.3%		25%		**41.7%**	
	Gen. X	103	11 (10.7%)	11 (10.7%)	14 (13.6%)	17 (16.5%)	22 (21.4%)	10 (9.7%)	18 (17.5%)
				35.0%		16.5%		**48.6%**	
	Gen. Y	131	6 (4.6%)	13 (9.9%)	18 (13.7%)	42 (32.1%)	25 (19.1%)	18 (13.7%)	9 (6.9%)
				28.2%		32.1%		**39.7%**	
	Gen. Z	17	1 (5.9%)	5 (29.4%)	2 (11.8%)	1 (5.9%)	4 (23.5%)	3 (17.6%)	1 (5.9%)
				47.1%		5.9%		**47%**	

Appendix4

Obtained Gratifications		Likert Scale (1-Strongly Disagree – 7-Strongly Agree)							
		N	1	2	3	4	5	6	7
Information	Silver S.	12	0	0	0	1	3	2	6
			(0%)	(0%)	(0%)	(8.3%)	(25.0%)	(16.7%)	(50%)
				0%		8.3%		**91.7%**	
	Gen. X	105	2	5	5	4	24	15	50
			(1.9%)	(4.8%)	(4.8%)	(3.8%)	(22.9%)	(14.3%)	(47.6%)
				11.5%		3.8%		**84.8%**	
	Gen. Y	131	3	3	9	19	34	24	39
			(2.3%)	(2.3%)	(6.9%)	(14.5%)	(26.0%)	(18.3%)	(29.8%)
				11.5%		14.5%		**74.1%**	
	Gen. Z	17	0	0	0	0	5	6	6
			(0%)	(0%)	(0%)	(0%)	(29.4%)	(35.3%)	(35.3%)
				0%		0%		**100%**	
Self-Presentation	Silver S.	11	3	1	0	0	4	2	1
			(27.3%)	(9.1%)	(0%)	(0%)	(36.4%)	(18.2%)	(9.1%)
				36.4%		0%		**63.7%**	
	Gen. X	88	19	11	11	10	13	5	19
			(21.6%)	(12.5%)	(12.5%)	(11.4%)	(14.8%)	(5.7%)	(21.6%)
				46.6%		11.4%		42.1%	
	Gen. Y	113	21	18	19	15	18	6	16
			(18.6%)	(15.9%)	(16.8%)	(13.3%)	(15.9%)	(5.3%)	(14.2%)
				51.3%		13.3%		35.4%	
	Gen. Z	15	2	2	1	2	3	4	1
			(13.3%)	(13.3%)	(6.7%)	(13.3%)	(20.0%)	(26.7%)	(6.7%)
				33.3%		13.3%		**53.4%**	
Socialization	Silver S.	11	1	0	2	3	1	2	2
			(9.1%)	(0%)	(18.2%)	(27.3%)	(9.1%)	(18.2%)	(18.2%)
				27.3%		27.3%		**45.5%**	
	Gen. X	91	13	7	10	15	14	10	22
			(14.3%)	(7.7%)	(11.0%)	(16.5%)	(15.4%)	(11.0%)	(24.2%)
				33%		16.5%		**50.6%**	
	Gen. Y	121	14	12	12	31	16	18	18
			(11.6%)	(9.9%)	(9.9%)	(25.6%)	(13.2%)	(14.9%)	(14.9%)
				31.4%		25.6%		**43.0%**	
	Gen. Z	16	3	1	3	0	3	3	3
			(18.8%)	(6.3%)	(18.8%)	(0%)	(18.8%)	(18.8%)	(18.8%)
				43.9%		0%		**56.4%**	
Entertainment	Silver S.	12	1	1	1	3	3	1	2
			(8.3%)	(8.3%)	(8.3%)	(25.0%)	(25.0%)	(8.3%)	(16.7%)
				24.9%		25.0%		**50.0%**	
	Gen. X	98	11	6	8	17	20	14	22
			(11.2%)	(6.1%)	(8.2%)	(17.3%)	(20.4%)	(14.3%)	(22.4%)
				25.5%		17.3%		**57.1%**	
	Gen. Y	127	4	12	17	35	27	14	18
			(3.1%)	(9.4%)	(13.4%)	(27.6%)	(21.3%)	(11.0%)	(14.2%)
				25.9%		27.6%		**46.5%**	
	Gen. Z	16	0	2	4	2	3	3	2
			(0%)	(12.5%)	(25.0%)	(12.5%)	(18.8%)	(18.8%)	(12.5%)
				37.5%		12.5%		**50.1%**	

Appendix5

Self-Determination				Likert Scale (1-Strongly Disagree – 7-Strongly Agree)						
Motivation	Regulation		N	1	2	3	4	5	6	7
Extrinsic	External	Male	24	20 (83.3%)	3 (12.5%)	0 (0%)	0 (0%)	0 (0%)	0 (0%)	1 (4.2%)
					95.8%		0%		4.2%	
		Female	240	228 (95.0%)	1 (0.4%)	0 (0%)	1 (0.4%)	2 (0.8%)	0 (0%)	8 (3.3%)
					95.4%		0.4%		4.1%	
	Introjected	Male	24	19 (79.2%)	3 (12.5%)	0 (0%)	1 (4.2%)	0 (0%)	0 (0%)	1 (4.2%)
					91.7%		4.2%		4.2%	
		Female	240	220 (91.7%)	8 (3.3%)	2 (0.8%)	1 (0.4%)	0 (0%)	0 (0%)	9 (3.8%)
					95.8%		0.4%		3.8%	
	Identified	Male	24	5 (20.8%)	3 (12.5%)	5 (20.8%)	4 (16.7%)	1 (4.2%)	5 (20.8%)	1 (4.2%)
					54.1%		16.7%		29.2%	
		Female	231	45 (19.5%)	34 (14.7%)	20 (8.7%)	46 (19.9%)	29 (12.6%)	30 (13.0%)	27 (11.7%)
					42.9%		19.9%		37.3%	
	Integrated	Male	23	7 (30.4%)	3 (13.0%)	1 (4.3%)	5 (21.7%)	4 (17.4%)	3 (13.0%)	0 (0%)
					47.7%		21.7%		30.4%	
		Female	205	47 (22.9%)	24 (11.7%)	28 (13.7%)	46 (22.4%)	28 (13.7%)	17 (8.3%)	15 (7.3%)
					48.3%		22.4%		29.3%	
Intrinsic	Intrinsic	Male	24	0 (0%)	4 (16.7%)	4 (16.7%)	3 (12.5%)	3 (12.5%)	4 (16.7%)	6 (25.0%)
					33.4%		12.5%		**54.2%**	
		Female	239	7 (2.9%)	8 (3.3%)	16 (6.7%)	37 (15.5%)	55 (23.0%)	53 (22.2%)	63 (26.4%)
					12.9%		15.5%		**71.6%**	
Amotivation ("Boredom")	Non-Regulation	Male	24	14 (58.3%)	2 (8.3%)	3 (12.5%)	1 (4.2%)	2 (8.3%)	1 (4.2%)	1 (4.2%)
					79.1%		4.2%		16.7%	
		Female	227	127 (55.9%)	39 (17.2%)	13 (5.7%)	20 (8.8%)	17 (7.5%)	4 (1.8%)	7 (3.1%)
					78.8%		8.8%		12.4%	
Amotivation ("Just for heck of it")	Non-Regulation	Male	24	6 (25.0%)	5 (20.8%)	0 (0%)	7 (29.2%)	3 (12.5%)	0 (0%)	3 (12.5%)
					45.8%		29.2%		25.0%	
		Female	235	74 (31.5%)	28 (11.9%)	21 (8.9%)	27 (11.5%)	27 (11.5%)	26 (11.1%)	32 (13.6%)
					52.3%		11.5%		36.2%	

Appendix6

Self-Determination				Likert Scale (1-Strongly Disagree – 7-Strongly Agree)						
Motivation	**Regulation**		**N**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Extrinsic	External	Silver S.	12	11	0	0	1	0	0	0
				(91.7%)	(0%)	(0%)	(8.3%)	(0%)	(0%)	(0%)
					91.7%		8.3%		0%	
		Gen. X	103	97	1	0	0	0	0	5
				(94.2%)	(1.0%)	(0%)	(0%)	(0%)	(0%)	(4.9%)
					95.2%		0%		4.9%	
		Gen. Y	133	124	3	0	0	2	0	4
				(93.2%)	(2.3%)	(0%)	(0%)	(1.5%)	(0%)	(3.0%)
					95.5%		0%		4.5%	
		Gen. Z	17	17	0	0	0	0	0	0
				(100%)	(0%)	(0%)	(0%)	(0%)	(0%)	(0%)
					100%		0%		0%	
	Introjected	Silver S.	12	12	0	0	0	0	0	0
				(100%)	(0%)	(0%)	(0%)	(0%)	(0%)	(0%)
					100%		0%		0%	
		Gen. X	103	94	2	0	1	0	0	6
				(91.3%)	(1.9%)	(0%)	(1.0%)	(0%)	(0%)	(5.8%)
					93.2%		1.0%		5.8%	
		Gen. Y	133	119	9	0	1	0	0	4
				(89.5%)	(6.8%)	(0%)	(0.8%)	(0%)	(0%)	(3.0%)
					96.3%		0.8%		3.0%	
		Gen. Z	17	15	0	2	0	0	0	0
				(88.2%)	(0%)	(11.8%)	(0%)	(0%)	(0%)	(0%)
					100%		0%		0%	
	Identified	Silver S.	12	1	2	2	5	0	1	1
				(8.3%)	(16.7%)	(16.7%)	(41.7%)	(0.0%)	(8.3%)	(8.3%)
					41.7%		**41.7%**		16.6%	
		Gen. X	101	26	14	11	15	8	13	14
				(25.7%)	(13.9%)	(10.9%)	(14.9%)	(7.9%)	(12.9%)	(13.9%)
					50.5%		14.9%		34.7%	
		Gen. Y	126	22	18	10	26	20	17	13
				(17.5%)	(14.3%)	(7.9%)	(20.6%)	(15.9%)	(13.5%)	(10.3%)
					39.7%		20.6%		**39.7%**	
		Gen. Z	17	1	3	2	4	2	5	0
				(5.9%)	(17.6%)	(11.8%)	(23.5%)	(11.8%)	(29.4%)	(0%)
					35.3%		23.5%		**41.2%**	
	Integrated	Silver S.	12	2	1	2	3	2	2	0
				(16.7%)	(8.3%)	(16.7%)	(25.0%)	(16.7%)	(16.7%)	(0%)
					41.7%		25.0%		33.4%	
		Gen. X	93	26	12	12	17	10	9	7
				(28.0%)	(12.9%)	(12.9%)	(18.3%)	(10.8%)	(9.7%)	(7.5%)
					53.8%		18.3%		28%	
		Gen. Y	109	23	13	14	25	19	7	8
				(21.1%)	(11.9%)	(12.8%)	(22.9%)	(17.4%)	(6.4%)	(7.3%)
					45.8%		22.9%		31.1%	
		Gen. Z	15	3	1	1	7	1	2	0
				(20.0%)	(6.7%)	(6.7%)	(46.7%)	(6.7%)	(13.3%)	(0%)
					33.4%		**46.7%**		20%	
Intrinsic	Intrinsic	Silver S.	12	0	0	0	0	4	3	5
				(0%)	(0%)	(0%)	(0%)	(33.3%)	(25.0%)	(41.7%)
					0%		0%		**100%**	
		Gen. X	103	6	6	8	13	20	23	27
				(5.8%)	(5.8%)	(7.8%)	(12.6%)	(19.4%)	(22.3%)	(26.2%)
					19.4%		12.6%		**67.9%**	
		Gen. Y	132	1	5	11	21	31	29	34
				(0.8%)	(3.8%)	(8.3%)	(15.9%)	(23.5%)	(22.0%)	(25.8%)
					12.9%		15.9%		**71.3%**	
		Gen. Z	17	0	1	1	6	3	3	3
				(0%)	(5.9%)	(5.9%)	(35.3%)	(17.6%)	(17.6%)	(17.6%)
					11.8%		35.3%		**52.8%**	

Self-Determination				Likert Scale (1-Strongly Disagree – 7-Strongly Agree)						
Motivation	**Regulation**		**N**	**1**	**2**	**3**	**4**	**5**	**6**	**7**
Amotivation (“Boredom”)	Non-Regulation	Silver S.	12	10	1	0	1	0	0	0
				(83.3%)	(8.3%)	(0%)	(8.3%)	(0%)	(0%)	(0%)
					91.6%		8.3%		0%	
		Gen. X	100	64	14	6	3	8	2	3
				(64.0%)	(14.0%)	(6.0%)	(3.0%)	(8.0%)	(2.0%)	(3.0%)
					84%		3.0%		13%	
		Gen. Y	123	57	24	9	16	9	3	5
				(46.3%)	(19.5%)	(7.3%)	(13.0%)	(7.3%)	(2.4%)	(4.1%)
					73.1%		13%		13.8%	
		Gen. Z	17	11	2	1	1	2	0	0
				(64.7%)	(11.8%)	(5.9%)	(5.9%)	(11.8%)	(0%)	(0%)
					82.4%		5.9%		11.8%	
Amotivatin (“Just for heck of it”)	Non-Regulation	Silver S.	12	5	0	1	2	2	1	1
				(41.7%)	(0%)	(8.3%)	(16.7%)	(16.7%)	(8.3%)	(8.3%)
					50%		16.7%		33.3%	
		Gen. X	102	35	10	5	15	11	11	15
				(34.3%)	(9.8%)	(4.9%)	(14.7%)	(10.8%)	(10.8%)	(14.7%)
					49%		14.7%		36.3%	
		Gen. Y	128	34	20	14	16	16	11	17
				(26.6%)	(15.6%)	(10.9%)	(12.5%)	(12.5%)	(8.6%)	(13.3%)
					53.1%		12.5%		34.4%	
		Gen. Z	17	6	3	1	1	1	3	2
				(35.3%)	(17.6%)	(5.9%)	(5.9%)	(5.9%)	(17.6%)	(11.8%)
					58.8%		5.9%		35.3%	

Part III

Self-Quantified Privacy-Related Behavior and Concerns

7 How Do Users of Activity Tracking Technologies Perceive the Data Privacy Environment in the EU?

Fietkiewicz, K. J., & Ilhan, A. (2020). How do users of activity tracking technologies perceive the data privacy environment in the EU? *iConference 2020 Poster Proceedings*.

Abstract *With the omnipresent digitalization and quantification of our everyday life, data privacy became an important topic in research, politics and legislation. In order to contain the possible risks of uncontrolled data collection and its possible misuse, it is important to ensure a sustainable data privacy environment. Here, one of the most important aspects is an efficient and effective legislature. In May 2018, when the General Data Protection Regulation GDPR came into force, the EU made an important step towards improving the European data privacy environment. In this study there are investigated both, the awareness and the perception of the GDPR by the users of fitness tracking technologies. This investigation focuses on people from the EU using a fitness tracking application as well as a fitness tracking device, which usually collect a lot of personal and health-related data. Most of the fitness tracking users are aware of the GDPR but do not believe that it will improve the reality of data privacy. Even though there appears to be limited belief in the sustainability of the European data privacy environment (in terms of a positive development of consumers' data privacy), this does not necessarily affect the everyday usage of activity tracking applications and wearables.*

7.1 Introduction

Data privacy concerns rise with the increasing digitalization and quantification of our everyday life. What changes is also our information behavior, which now includes storing countless (personal) information pieces on the web and cloud services. These also include health information collected with activity tracking technologies, such as mobile fitness applications or fitness tracking wearables. The increasing pace of technological development is accompanied by the uncertainty about where it will lead and, especially, how all the collected data could be exploited (since it is already seen as a form of "currency" (Fietkiewicz & Lins, 2016)). Facing these uncertain future developments, it is important to create a more sustainable data privacy environment, comprised of adequate legal framework, its effective enforcement, and compliance by the business enterprises. Fitness tracking technologies can collect diverse personal, health-related, or location-based data, therefore, this is a prominent sector to investigate in the context of data privacy environment.

Fitness tracking is also popular in the scientific field. Most studies on this topics focus on the accuracy of the trackers (see, e.g., Evenson, Goto, & Furberg, 2015; Rosenberger, Buman, Haskell, McConnell, & Carstensen, 2016) or usability, engagement, adoption, and acceptance (see, e.g., Feng, Li, & Agosto, 2017; Fritz, Huang, Murphy, & Zimmermann, 2014; Gouveia, Karapanos, & Hassenzahl, 2015; Ilhan & Henkel, 2018; Lyall & Robards, 2018; Nelson, Verhagen, & Noordzij, 2016; Rooksby, Rost, Morrison, & Chalmers, 2014). The number of studies on activity tracking technologies increased over the last years, which was confirmed by the systematic literature review (2013-2017) conducted by Shin et al. (2019). Based on a topic modeling analysis, Shin et al. (2019) were able to detect six thematic clusters, "privacy" being one of them. Fietkiewicz and Henkel (2018) conducted a literature review on fitness tracking and data privacy in the context of the GDPR. They point out several research gaps that could be closed in future studies, including a more extensive user-oriented research that goes beyond users' privacy preferences. The scientific coverage of activity tracking and data privacy is still limited and mostly investigated from the technological point of view (e.g., encryption of health-related data, (see Abbas & Khan, 2014; Fernández-Alemán, Señor, Lozoya, P. Á. O., & Toval, 2013; Li, Wu, Gao, & Shi, 2016). Therefore, this study focuses on users' knowledge and attitude towards European data privacy environment.

Considering data privacy in the EU, since May 2018 the GDPR plays a crucial role in regulating the consumer market, also for the fitness tracking industry. GDPR came into force in order to improve the security of personal data of the European consumers and, among others, to empower them to decide about what happens to their data. There already are few studies investigating the compliance of mobile applications with the GDPR (Benjumea, Dorronzoro, Ropero, Rivera-Romero, & Carrasco, 2019; Braghin, Cimato, & Libera, 2018; Muchagata & Ferreira, 2018, 2019). Even though in these studies the focus is set on mobile health applications (mHealth), the data collected by such applications is to a certain extent similar to the data accumulated through fitness or activity tracking. The new legislation might improve the data privacy environment in EU by making it more effective and sustainable. Some of GDPR's requirements are: explicit consent of the consumers to collect, use and move their data; the right to be forgotten; mandatory data preach notifications (within 72 hours); or privacy by design (Braghin et al., 2018). The press release of the European Commission (May, 22 2019) (European Commission, 2019) indicates that already within about one year since GDPR came into force, "people are starting to use their new rights and more than two-third of Europeans have heard of the regulations." However, it should not only be considered whether consumers have heard of GDPR, but also what is their perception of the regulation and its impact on data privacy. The recent research focuses only on the compliance of mobile health applications with the new legislation (which seems to be not fully satisfactory, see e.g. (Benjumea et al., 2019; Muchagata & Ferreira, 2019), but does not consider the perception of it by users of these applications. This rises the research questions (RQs) for the current study:

RQ1: How is the awareness of the GDPR among users of activity tracking technologies in the EU?
RQ2: Do the users of activity tracking technologies expect the GDPR to change the status of data protection for the better?

This research does not evaluate the sustainability of the GDPR, but rather how it is being perceived by the consumers. Given the requirement of "privacy by design" or "privacy by default," the regulation seems to be more sustainable than the preceding Data Privacy Directive. Now, data privacy has to be considered as early as during the development stages of the technology and the amount of data collected "by default" needs to be kept to a needed minimum. However, are the European fitness tracking consumers convinced of this regulation's effectiveness?

7.2 Methods

Online Questionnaire The online survey conducted for this study included different blocks of questions, some of which were not privacy-related (e.g., socio-demographic questions, general activity and fitness level, use and duration of activity tracking applications and devices). Considering the research gaps indicated in the introduction, this study focuses only on GDPR and privacy-related aspects as well as the activity tracking technology users from the EU. The remaining study participants (non-users, or users from other regions) as well as other questions not related to privacy, which were included in the survey, will not be further elaborated from this point on.

The survey included the question about the awareness of as well as the general opinion on GDPR. As the survey was also accessible to participants from non-EU countries, the answer "I am not from EU, so it does not concern me" was added. Furthermore, three statements addressing the general opinion on online data privacy (GO1-GO3) were also included to investigate, if a positive or negative expectation of GDPR vary significantly between users with different opinions on general online data privacy. This opinion could be marked on a five-point Likert scale from '1—Strongly Disagree' to '5—Strongly Agree' and the neutral element '3—Neither agree nor disagree.'

A pretest of the survey by six participants led to minor modifications in language, formulating statements more objectively, clarifying any ambiguities, adding open questions for further comments, and making the survey more user-friendly by different positioning and segmentation of the questions. The survey distribution was non-probabilistic with a self-selected set of respondents. It distributed from February 26, 2019, until May 28, 2019, through different social media channels, scientific communities, or survey portals (e.g., SurveyCircle, Survey Tandem).

7.3 Results

All in all, 646 participants completed the survey, but only 235 currently use both, a fitness application and an activity tracker or smartwatch. Furthermore, 167 of these participants were from the EU (which is the relevant sample for the current study). The most represented EU-countries were Germany, U.K., Poland and Austria. In general, activity trackers and applications by the companies Fitbit, Garmin and Apple were the most popular among the study participants. The distribution by gender is very balanced (Table 7.1) as 49.7% of the participants are female, and 50.3% are male. Regarding the age of the participants, for further analysis a categorization into four generations, based on research on inter-generational differences in digital media usage (Fietkiewicz, 2017), was conducted. The four generations include: Silver Surfers (at least 60 years old), Gen X (40-59 years old), Gen Y (between 24 and 39 years old), and finally, Gen Z (up to 23 years old). As for this sample, the biggest age group is Gen Y (63.5%) and Gen X (21%).

Table 7.1: Sample characteristics: fitness trackers and fitness applications' users from the EU.

Sample characteristics (N=167)	
Gender	Male 50.3% (n=84)
	Female 49.7% (n=83)
Age	Silver Surfers 6.6% (n=11)
	Gen X 21% (n=35)
	Gen Y 63.5% (n=106)
	Gen Z 9% (n=15)
Avg. activity level during the day	3 ("I am moderately active")
Avg. exercise level	7 ("I exercise 3 or more times per week")
Avg. usage freq. of application	7 ("Every day")
Avg. usage duration of application	4 ("For a year")
Avg. usage freq. of wearable	7 ("Every day")
Avg. usage duration of wearable	4 ("For a year")

The first research question concerned the users' awareness of the GDPR, whereas the second research question regarded their perception of GDPR's effectiveness. A total 95% of the survey participants from EU heard of the GDPR. More than half of these users (61%; N=158) do not think that it will change anything for consumers' data privacy. Interestingly, one participant mentioned that "[mainly] it would be about privacy. Although GDPR is a good thing, many companies will not obey the rules because there is a lot of money to be made in selling this data. Even the UK government is selling on confidential patient data to industry" (participant$_1$).

The participants' attitude towards GDPR was further analyzed in the context of their general data privacy concerns. Figure 7.1 shows that all in all users from the EU are concerned about data security on the Internet and about what companies can do with their data. Even though GDPR is supposed to protect consumer data, users from the EU are still doubtful about its effectiveness.

A Mann-Whitney U test was applied to determine if there were significant differences in general online data privacy concerns between EU users who believe in the effectiveness of GDPR and the ones who do not. Distributions of each statement (GO1-3) for users who think positively and negatively about GDPR were quite similar considering the median values, except for GO3. Here, the mean ranks are significantly different between users who believe in GDPR's effectiveness (Mean Rank = 85.97) and the more skeptical ones (Mean Rank = 63.77) ($U = 3125.500$, $z = 3.243$, $p = .001$). The median of "I feel safe about my personal data, because European data privacy regulations are sufficiently protecting my privacy" (GO3) is somewhat

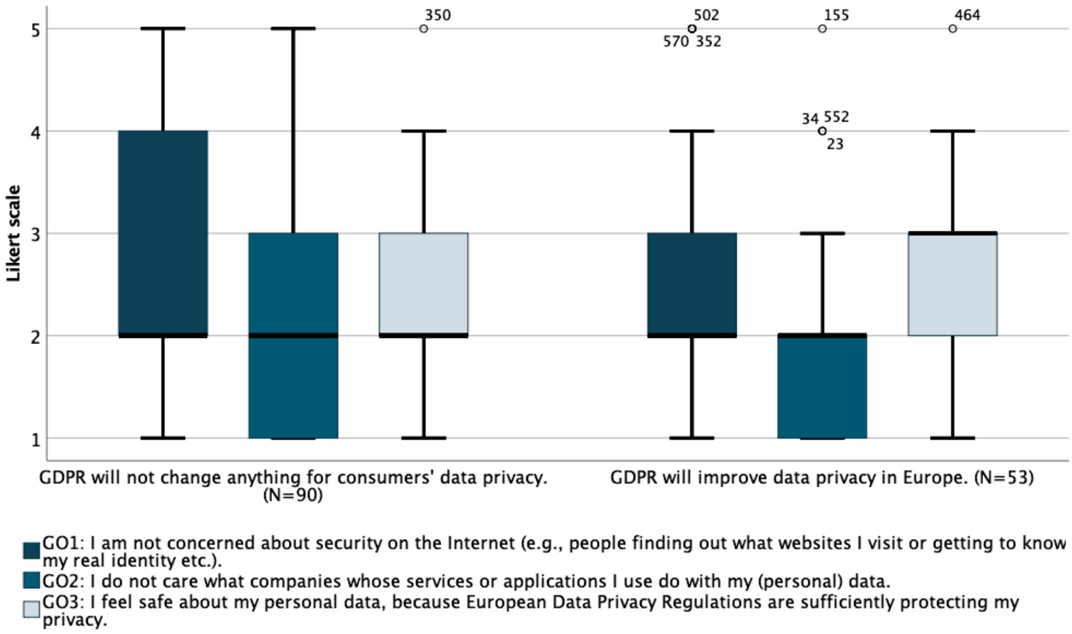

Figure 7.1: General opinion on online data privacy and GDPR. Likert scale from '1—Strongly Disagree' to '5—Strongly Agree

higher for the reserved (impartial) users (Median = 3; 'Neither agree nor disagree') than for the skeptical ones (Median = 2; 'Disagree'). This is a somehow expected outcome, since people who are in general skeptical about the effectiveness of European data privacy legislation have most probably some reservations towards the GDPR. Hence, the new legislation does not seem to have convinced the skeptics. Interestingly, when considering the distribution of the answers, participants who hope to see improvement due to the GDPR are partly more concerned about online data privacy than the other group.

The differences between GDPR enthusiasts and GDPR skeptics were further analyzed in the context of their socio-demographic characteristics as well as fitness (tracking) routine. In Table 7.2 we can see some slight differences, e.g., that more women are skeptical about GDPR than men, or that the older generations are more likely to disbelieve in its effectiveness than the younger ones. However, Pearson Chi2 revealed that there is no significant association between any of these variables and the attitude towards GDPR.

Furthermore, there appear to be no differences between these two groups regarding their activity and fitness (tracking) level. This was also confirmed by the Mann-Whitney U Test. It seems that mistrust in the data privacy environment does not get influenced by the usage of fitness tracking technologies, or vice versa, it does not influence it in any apparent way.

Table 7.2: Differences between GDPR enthusiasts and pessimists (n=143).

		GDPR enthusiasts (n=53)	**GDPR pessimists (n=90)**
Gender	Male	45.7%	54.3%
	Female	31.2%	68.8%
Age	Silver Surfers	30%	70%
	Gen X	38.2%	61.8%
	Gen Y	37.6%	62.4%
	Gen Z	53.8%	46.2%
Activity Level	During the day	3 (moderate)	3 (moderate)
	Exercise	7 (3< times/week)	6 (1-2 times/week)
Activity application	Usage freq.	7 (every day)	7 (every day)
	Usage duration	4 (for a year)	4 (for a year)
Activity wearable	Usage freq.	7 (every day)	7 (every day)
	Usage duration	4 (for a year)	4 (for a year)

7.4 Discussion

This study showed that users of the fitness tracking applications and activity wearables from the EU are mostly aware of the GDPR. Interestingly, the results also show that more than half of these participants do not believe that it will lead to positive changes considering data protection. As one participant mentioned, one critical aspect is trust in its impact and perseverance. Users need to be able to trust in the effectiveness of the legal system and that the companies will comply. Some statements made by the users (even those who are not living in the EU) indicated that the EU has better data protection conditions than non-EU countries. Considering data scandals in the last years, it seems that users need more effective data protection regulations and their consistent execution. But, it is also not very surprising that users who believe in the effectiveness of European data privacy regulations are more likely to believe in the effectiveness of the new GDPR (or at least have a “neutral” opinion about it, as opposed to users who “disagree” with the efficacy of European legislation).

The implications of presented results are limited as the study only investigated whether participants are aware of the GDPR and whether they think it will positively change the state of data protection, but not why they think so or what impact it has on the fitness tracking industry in particular. This could be an interesting aspect to investigate in future research.

7.5 Conclusion

The aim of this study was to do a first step towards closing the research gap in the domain of fitness tracking and sustainable data privacy environment, which up until now focused on the technological point of view. For this reason, we conducted a user-centered survey and gained insights into fitness tracking application users' awareness and attitude towards GDPR. Even though the participating European users are aware of the GDPR, most of them are rather skeptical as to its impact on data privacy. This however, does not appear to be impacted by socio-demographics aspects as well as the extent of the usage of fitness tracking technology.

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8 Fitness Tracking Technologies: Data Privacy Doesn't Matter? The (Un)Concerns of Users, Former Users, and Non-Users

Fietkiewicz, K. J., & Ilhan, A. (2020). Fitness tracking technologies: data privacy doesn't matter? The (un)concerns of users, former users and non-users. In *Proceedings of the 53rd Hawaii International Conference on System Sciences, January 7-10, 2020, Grand Wailea, Maui* (pp. 3439-3448). ScholarSpace.

Abstract *To be concerned about data privacy in the fitness tracking world is apparently not the question of age or fitness level. It also does not necessarily influence the actual use of fitness tracking technologies. In this empirical study, 590 participants from the EU and USA, who are current users, former users or non-users of fitness tracking applications, were surveyed (online) on their sensitivity perception of several data pieces collected with fitness trackers as well as their data privacy concerns. Furthermore, subgroups of different fitness tracking users were detected based on their different privacy unconcerns.*

8.1 Introduction

Today, ubiquitous technologies spread rapidly in different spheres of our lives. Even though the use of these technologies is not forced on anybody, the shift towards increased application of digital goods and new trends appears omnipresent and somewhat inevitable. The adoption of these new trends can be based on genuine interest or gained benefits, but also on social pressure or the need to belong. Depending on many factors, the usage of these technologies might feel safe and solely beneficial or it can be accompanied by uneasy feeling, e.g., of being dependent, surveilled or, in general, uncertain of the security of personal data collected or generated with this technology. One good example are the users of fitness tracking and similar wearable technologies, who apply them while often having many concerns about privacy risks. Still, in order to profit from the (fitness and health) benefits, they need to accept the challenges and threats. Data privacy and security became one of the prominent concerns in this area, especially since wearable technology encourages collection, storage and sharing of health-related data, which might be perceived as more sensitive than the usual name-gender-age information, nowadays rather willingly shared on many social networks.

Even though the fitness tracking tools give (health and fitness-related) benefits to the consumers, they also pose new and partially unpredictable challenging threats to data privacy and security. These threats exist due to the possibility of ubiquitous collection of large amounts of data in real time and creation of detailed user behavior patterns, e.g., when people eat, sleep (and how good or bad), exercise or go home from work (Patterson, 2013). The new tracking devices and applications are collecting both, personal information as well as health data, and create "a quantified self for their users," which becomes especially risky when the companies (being in custody of users' data) might violate their privacy and misuse it (Motti & Claine, 2015)(Stach, 2018, p. 13).

Activity tracking technologies are collecting different kinds of data (e.g., steps, heart rate, sleep stages, geolocation), which might be considered to have different degrees of sensitivity. This led Lidynia, Brauner, and Ziefle (2018) to investigate the users' perceived sensitivity of different data types. They online-surveyed 82 participants from Germany, where 46 participants were characterized as non-users of wearables and 36 participants as wearable users. Their results show that data types such as GPS, sleep analysis, and weight are perceived as (rather) sensitive in comparison to, for example, step count, hours spent standing, and the number of climbed stairs. Lehto and Lehto (2017) investigated the user perception of privacy and sensitivity of health information collected with wearable devices as well as their willingness to share such information with other parties. The participants of their qualitative study "described the information collected by their devices as not sensitive, not secret, not confidential, and quite general" (Lehto & Lehto, 2017, p. 247). Even though the collected information was not perceived as sensitive, some interviewees expressed concerns when the data should be connected with individual's name and address.

Previous studies showed that people are mainly concerned about the collection of GPS data (Klasnja, Consolvo, Choudhury, Beckwith, & Hightower, 2009; Motti & Claine, 2015; Nissenbaum, 2011) as well as data about their mood or stress level (Nissenbaum, 2011; Peppet, 2014) and the detailed health information (Nissenbaum, 2011). This topic attracts attention also outside the scientific community. For example, last year, The Guardian reported about the case "Fitness tracking app Strava gives away location of secret US army bases" (Hern, 2018). Even though this breach was not concerning data collected by daily users or runners, it again showed the sensitivity of information pieces obtained through different fitness applications and which potential risks might be lurking (Hern, 2018). Although people seem to agree on sensitivity of location or detailed health data, the users of fitness trackers do not express one specific privacy concern about data collection on their device, as it appears to change depending on various factors (Gorm & Shklovski, 2016; Klasnja et al., 2009; Motti & Claine, 2015; Vitak, Liao, Kumar, Zimmer, & Kritikos, 2018). Lower concerns or even unconcerns can be explained by the lacking awareness of how users' privacy can be compromised due to collection of "granular data about users over a long time" (Vitak et al., 2018, p. 230).

In order to identify how do former and current user as well as non-users of fitness tracking applications perceive sensitivity of several data types collected by this technology, we formulate the first research question **(RQ1)**: What is the perceived sensitivity of different data types by current users, former users, and non-users of the fitness tracking applications?

Not without reason, many users of tracking apps have concerns about privacy protection (Lieffers, Vance, & Hanning, 2014), third party access to data (Dennison, Morrison, Conway, & Yardley, 2013), as well as access to personal information by apps (Chen, Bauman, & Allmann-

Farinelli, 2016). Still, even when users understand and care about potential data privacy risks, "they feel that once information is shared, it is ultimately out of their control. They attribute this to the opaque practices of institutions, the technological affordances of social media, and the concept of networked privacy, which acknowledges that individuals exist in social contexts where others can and do violate their privacy" (Hargittai & Marwick, 2016, p. 3738).

Fitness tracking technologies are popular not only among the consumers, but also researchers on human-computer interaction and health informatics. The number of studies on activity tracking technologies increased over the last years (Shin et al., 2019). Recently, it focuses more on the ubiquitous data collection and privacy (Ball, Domenico, & Nunan, 2016; Christovich, 2015; Crawford, Lingel, & Karppi, 2015; Patterson, 2013; Peppet, 2014). Due to the "mobile and networked nature of fitness trackers [...] they automatically and persistently collect data, which companies share with or sell to third parties" (Vitak et al., 2018, p. 230). Although seemingly anonymous, the collected user data can be more easily re-identified due to the increasing uniqueness of the datasets (Grundy, Held, & Bero, 2017; Patterson, 2013).

There is scientific interest in users' behaviors when sharing the so-called personal fitness information and the privacy concerns coming from the collection, aggregation, and sharing of these information pieces (Vitak et al., 2018, p. 229). How sensitive do people perceive their fitness information to be? And what data privacy concerns do they have? These questions are increasingly discussed in context of the so-called privacy paradox (Ball et al., 2016; Brashear, Milne, & Kashyap, 2006; Christovich, 2015), meaning that even though users express some privacy concerns, they "behave in ways that appear to undermine their privacy" (Vitak et al., 2018, p. 230).

Based on the disagreement regarding what privacy concerns about fitness tracking technology do users and non-users indeed have, we formulated the second research question **(RQ2)**: What are the general privacy concerns about fitness tracking by current users, former users, and non-users of the fitness tracking applications?

Finally, previous research indicates that some users apply fitness tracking applications to the fullest extent even though they have data privacy-related concerns (so-called privacy paradox). Also, there are users who do not voice any specific concerns about the fitness tracking technologies. Hence, there appear to exist different groups of fitness tracking users when considering the state of (perceived) data sensitivity and security. This leads us to the final research question **(RQ3)**: What types of fitness tracking applications' users can we distinguish based on their data privacy concerns?

8.2 Methods

In order to collect suitable data for this study, an online survey was conducted. This way it was possible to reach as many participants from the European Union and the USA as possible. The origin of fitness tracking users can impact their attitude towards data privacy (Bellman, Johnson, Kobrin, & Lohse, 2004; Brashear et al., 2006; Miltgen & Peyrat-Guillard, 2014) and should be considered as an influencing factor during the interpretation of the results; especially considering the fundamentally different data protection history and regulations in the USA and the EU (Fietkiewicz, Lins, Baran, & Stock, 2016). The survey targeted not only current users of fitness tracking technologies, but also former users and non-users, who also might have data privacy concerns.

The online survey started with questions about the use of activity tracking applications and wearables, as well as their usage frequency and duration. Inquired was also the general opinion on (online) data privacy ("I am not concerned about security on the Internet, e.g. people finding out what websites I visit or getting to know my real identity," and "I do not care what companies whose services or applications I use do with my (personal) data"), which could be valued on a 5-point Likert scale. These questions provided data to include further factors possibly influencing privacy-related concerns about fitness tracking applications as well as the perceived sensitivity of data pieces collected by fitness tracking technology.

Seven items were formulated to inquire participants' data privacy-related concerns about fitness tracking applications (e.g., misuse of data by the company). The questions could also be answered on a 5-point Likert scale. Five of the seven items were adopted from Lidynia, Schomakers, and Ziefle (Lidynia, Schomakers, & Ziefle, 2019), who among others investigated the data privacy concerns of fitness tracking users and non-users in Germany. The other two items were added based on the research about involvement of heath insurances and possible third parties inferences (Henkel, Heck, & Göretz, 2018; Lehto & Lehto, 2017; Pingo & Narayan, 2018). All three types of participants (users, former users, and non-users of activity tracking applications) had to answer those questions.

In order to measure the perceived sensitivity of different data types, the following data pieces were adopted from the work by Lidynia, Brauner, and Ziefle (Lidynia et al., 2018, p. 45): "Step count," "Pulse,"* "GPS,"* "Calories,"* "Blood pressure," "Stairs,"* "Standing hours," "Sleep analysis,"* "BMI,"* "Blood sugar," and "Weight." Data pieces marked with "*" were labeled differently than in research by Lidynia et al. (2018) in order to clarify the meaning of the data pieces to the survey participants. Considering the functionalities of activity tracking technologies, further data pieces were added: menstrual cycle, completed workouts, fitness level/experience points, trophies, badges, lost and won challenges, real name, gender, birthday, e-mail, contacts/friends, and joined groups. All in all, the survey included 23 data pieces, which had to be assessed by all three groups of participants. The data pieces were grouped into the categories: personal data, health- related data, activity data and progress data. The rating scale for each data piece ranged from "1—not sensitive at all. I would make it public" to "5—Very sensitive. I don't want anyone to know it." Here, also the answer possibility "I don't know what it is" (especially for non- users) or "Not applicable" (e.g., information piece being "menstrual cycle" had to be answered by male participants) were included.

The survey was pretested by six participants, two non-users and four current or former users of activity tracking technologies. Three pretesters were males and three were females. After the pretest was concluded, the survey was slightly modified in regard to language (e.g., statements formulated more objectively), clarification of any ambiguities, adding of open questions for further remarks, and making the survey more user-friendly by different positioning and segmentation of the questions.

The online survey was non-probabilistically distributed from February 26, 2019, until May 28, 2019. It was spread through different social media channels, both private profiles and social media groups (e.g., Facebook, Reddit, Twitter, or Xing), scientific communities (ASIS&T), or portals for survey sharing (SurveyCircle, SurveyTandem).

The collected data was cleaned—incomplete answers and answers provided by pretesters were excluded, and the data was recoded into numerical values with the Syntax of IBM SPSS Statistics 25. The data collected from answers marked on the Likert scale was handled as ordinal.

In order to answer the first two research questions, the Kruskal-Wallis H Test and a subsequent post-hoc test were conducted to investigate the differences in perceived data sensitivity and data privacy concerns between three groups of participants (users, non-users, and former users of fitness tracking applications). Kruskal-Wallis H Test is a rank-based nonparametric test used to determine if there are statistically significant differences between two or more groups of an independent variable on a continuous or ordinal dependent variable (Laerd Statistics, 2018). It is adequate for our approach and collected data since the dependent variables (perceived data sensitivity and data privacy concerns) are measured on an ordinal scale. In order to determine which group(s) exactly are different from which other group(s), a post-hoc test—all pairwise comparisons using Dunn's (Dunn, 1964) procedure with a Bonferroni adjustment, was conducted (Laerd Statistics, 2018).

In order to determine the characteristics of possible subgroups of fitness tracking applications' users based on their perceived data sensitivity as well as data privacy concerns, the K-means clustering procedure was conducted. The K-means clustering algorithm was run for a range of K values in order to determine the most suitable one. Since the scale of the included ordinal variables ranges only from 1 to 5, the most distinctive group differences were given for $K=3$.

8.3 Results

Out of 777 online survey participants, 649 completed the survey (83.53%). Only participants who stated to be from the USA or the EU (N=590) were included in further analysis. The origin of fitness tracking users was considered as possibly influencing factor during the interpretation of the results.

The descriptive information about the sample is listed in Table 8.1. The distribution by gender is almost balanced (with 56% female participants). The survey addressed not only users of fitness tracking applications (55.9%), but also former users (9%) and non-users (35%). The age distribution is satisfactory, since both, elderly (over 60) and young adults (up to 23 years old), are represented within the sample. The participants of the survey had to indicate their year of birth. For further analysis a categorization into four generations, based on research on inter-generational differences in digital media usage (Fietkiewicz, 2017; Fietkiewicz et al., 2016), was conducted. The four generations include: Silver Surfers (born before 1959, hence at least 60 years old), Gen X (or Digital Immigrants, born between 1960 and 1979, hence 40-59 years old), Gen Y (also Digital Natives or Millennials, born between 1980 and 1995; between 24 and 39 years old), and finally, Gen Z (born after 1996, hence, up to 23 years old).

Table 8.1: Demographic information (N=590).

		Freq.	%
Origin			
	EU	477	80.8%
	USA	113	19.2%
Gender			
	Female	331	56.1%
	Male	253	42.9%
	Other	6	1.0%
Fitness Tracking Application			
	Current Users	330	55.9%
	Non-Users	207	35.1%
	Former Users	53	9.0%
Generation			
	Silver Surfers	55	9.3%
	Gen X	115	19.5%
	Gen Y	327	55.4%
	Gen Z	93	15.8%

The inclusion of non-users in the survey gives us a third perspective on the perceived data sensitivity and data privacy concerns with regard to fitness tracking. However, their answers can be influenced by further factors like inexperience with fitness tracking or disinterest in fitness activity in general. The possible distortion of the results by non-users' lacking knowledge about different data pieces etc. was minimized by inclusion of the answer possibility "I don't know".

In order to verify, if the participating non-users are at all physically active, which might have an influence on their attitude towards fitness tracking in general, the Kruskal-Wallis H Test was conducted to determine any significant differences between users, non-users, and former users regarding their "daily activity level" (from "predominantly not active, e.g., due to an office job," to "highly active") and their fitness or exercise intensity. As for the daily activity level (ranging from 1 to 5), the median equals 3 ("moderately active") for all three groups, there is, however, a significant difference in the distribution between current users (Mean Rank = 317.10) and non-users (Mean Rank = 263.31), $H(2) = 14.058$, $p = .001$. As for the question about how often do the participants exercise (frequency ranging from 1 to 8), the differences in medians are rather small. For current users the median equals 7 ("exercising 3 or more times per week"), whereas for former users and non-users the median equals 6 ("exercising 1-2 times per week"). There are, however, significant differences in the distributions, $H(2) = 36.268$, $p < .001$, between current users (Mean Rank = 327.70) and non-users (Mean Rank = 240.20) ($p < .001$) as well as between former users (Mean Rank = 310.98) and non-users (p

= .016). Even though there are significant differences in fitness or exercise activity, on average the non-users of fitness tracking technologies are still quite active (exercising 1-2 times per week), which indicates a general interest in fitness (just not fitness tracking).

8.3.1 Perceived data sensitivity (RQ1)

The first research question concerns the differences in perceived data sensitivity by users, non-users, and former users of the fitness tracking applications. The results of the Kruskal-Wallis H Test for perceived sensitivity of “personal data” (Table 8.2) indicates significant differences in distributions for only two data pieces— “gender” and “interest groups.” A post-hoc test revealed statistically significant differences between users and non-users in both cases. When looking at the mean perceived sensitivity values for all groups (medians), there are barely any differences, except for “gender.” The users and former users perceive those pieces of information as rather not sensitive, whereas non-users perceive them as neutral.

There are more significant differences in the distribution of the perceived sensitivity of health-related data (continued in Table 8.2). Except for the information about “menstrual cycle” (sensitive for all three groups), the perceived sensitivity of all remaining information pieces is different between users and non-users. Moreover, there is a significant difference between former users and non-users for the data pieces “heart rate” and “sleeping times.” When considering the mean perceived sensitivity, the non-users valued “calories intake” and “heart rate” higher than former and current users, who perceive them as neutral. Interestingly, current users and non-users perceive “blood pressure” and “sleeping times” as rather sensitive, whereas the former users have a neutral attitude towards them.

Regarding the activity and progress data, all three groups agree on high sensitivity of GPS data (median of 5 for all groups, no significant differences in distribution). For the remaining data pieces, there are significant differences between users and non-users, and additionally between former users and non-users for the information about “step count.” Except for GPS data, users and former users perceive all remaining activity and progress data as neutral (median of 3). Non-users also perceive most of the data pieces as neutral, except for the “step count” (interestingly seen as very sensitive, median equals 5), “fitness level or experience points” as well as “lost challenges” (rather sensitive, median equals 4). Interestingly, even though non-users perceive the information about “lost challenges” as rather sensitive, their perception of the information about “won challenges” is neutral (median equals 3).

Table 8.2: Differences in perceived sensitivity of different data pieces by mean ranks (MR) and medians (Mdn).

			Users (Y)	Non-Users (N)	Former Users (F)	Kruskal-Wallis H Test	Post-Hoc Test
Personal data	Real name	MR	277.53	312.17	287.42	$H(2) = 5.714$	
		Mdn	4 (n=325)	4 (n=202)	4 (n=53)	$p = .057$	-
	Gender	MR	274.20	322.87	277.81	$H(2) = 11.621$	Y - N
		Mdn	2 (n=327)	3 (n=203)	2.5 (n=52)	$p = .003$	$p = .002$
	Birthday	MR	281.14	310.42	283.34	$H(2) = 4.272$	-
		Mdn	4 (n=328)	4 (n=202)	4 (n=52)	$p = .118$	
	E-Mail	MR	296.76	280.21	302.07	$H(2) = 1.660$	
		Mdn	4 (n=327)	4 (n=202)	4 (n=53)	$p = .436$	-
	Contacts/ friends	MR	280.29	306.20	304.64	$H(2) = 4.264$	
		Mdn	5 (n=327)	5 (n=202)	5 (n=53)	$p = .119$	-
	Interest groups	MR	274.66	320.44	296.75	$H(2) = 10.042$	Y - N
		Mdn	4 (n=329)	4 (n=202)	4 (n=53)	$p = .007$	$p = .005$
Health-related data	Calories intake	MR	270.88	324.52	278.09	$H(2) = 13.835$	Y - N
		Mdn	3 (n=322)	4 (n=205)	3 (n=53)	$p = .001$	$p = .001$
	Burned calories	MR	269.87	331.45	287.00	$H(2) = 17.662$	Y - N
		Mdn	3 (n=327)	3 (n=205)	3 (n=53)	$p < .001$	$p < .001$
	Heart rate	MR	278.19	322.67	259.78	$H(2) = 11.496$	Y - N $p = .028$
		Mdn	3 (n=327)	4 (n=203)	3 (n=53)	$p = .003$	F - N $p = .038$
	Blood pressure	MR	275.28	320.23	270.50	$H(2) = 10.384$	Y - N
		Mdn	4 (n=325)	4 (n=202)	3 (n=53)	$p = .006$	$p = .006$
	Sleeping times	MR	280.13	321.51	256.34	$H(2) = 11.084$	Y - N $p = .013$
		Mdn	4 (n=326)	4 (n=205)	3 (n=53)	$p = .004$	F - N $p = .027$
	BMI	MR	274.76	320.40	299.55	$H(2) = 9.966$	Y - N
		Mdn	4 (n=327)	4 (n=205)	4 (n=53)	$p = .007$	$p = .005$
	Weight	MR	274.02	319.67	312.81	$H(2) = 10.686$	Y - N
		Mdn	4 (n=328)	4 (n=205)	4 (n=53)	$p = .005$	$p = .005$
	Menstrual cycle	MR	216.72	241.01	208.37	$H(2) = 5.113$	-
		Mdn	5 (n=244)	5 (n=159)	4 (n=45)	$p = .078$	

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			Users (Y)	Non-Users (N)	Former Users (F)	Kruskal-Wallis H Test	Post-Hoc Test
Activity & progress data	Step count	MR	209.15	404.51	254.40	H(2) = 175.95	Y - N p < .001
		Mdn	3 (n=329)	5 (n=159)	3 (n=53)	p < .001	F - N p < .001
	GPS	MR	281.70	305.09	300.15	H(2) = 3.584	-
		Mdn	5 (n=327)	5 (n=202)	5 (n=53)	p = .167	
	Climbed stairs	MR	265.09	335.07	302.46	H(2) = 23.264	Y - N
		Mdn	3 (n=327)	3 (n=205)	3 (n=53)	p < .001	p < .001
	Standing hours	MR	268.89	325.82	298.01	H(2) = 15.446	Y - N
		Mdn	3 (n=325)	3 (n=204)	3 (n=53)	p < .001	p < .001
	Completed workouts	MR	262.61	337.80	295.08	H(2) = 26.553	Y - N
		Mdn	3 (n=325)	3 (n=205)	3 (n=53)	p < .001	p < .001
	Fitness level, XPs	MR	260.09	325.45	285.78	H(2) = 20.278	Y - N
		Mdn	3 (n=320)	4 (n=196)	3 (n=53)	p < .001	p < .001
	Trophies, badges	MR	261.86	326.45	285.54	H(2) = 19.645	Y - N
		Mdn	3 (n=324)	3 (n=194)	3 (n=53)	p < .001	p < .001
	Lost challenges	MR	251.02	333.41	277.01	H(2) = 32.779	Y - N
		Mdn	3 (n=315)	4 (n=195)	3 (n=53)	p < .001	p < .001
	Won challenges	MR	256.40	324.08	279.34	H(2) = 22.092	Y - N
		Mdn	3 (n=315)	3 (n=195)	3 (n=53)	p < .001	p < .001

8.3.2 Data privacy-related concerns about fitness tracking applications (RQ2)

The second research question addresses differences in data privacy-related concerns (Table 8.3) about fitness tracking applications between current users, former users, and non-users of fitness tracking applications. The Kruskal-Wallis H Test revealed significant differences in distribution between some of the groups for all concerns, except for "health insurances will access my data and use it against me." For the remaining concerns there are significant differences in distributions for former users and non-users and additionally between current users and former users (for the concerns that "collected data is too sensitive" and "the app companies will forward my personal data to third parties"). Interestingly, the former users seem less concerned about the listed aspects and see most of them as neutral (median equals 3), except for the concern that "it will be possible to create an exact profile of my movements, habits or preferences," which they slightly agree with (median equals 4). The users and non-users on average agree with all the statements (median equals 4).

Table 8.3: Differences in data privacy concerns about fitness tracking by mean ranks (MR) and medians (Mdn).

Concerns about fitness tracking applications		Users (Y)	Non-Users (N)	Former Users U(F)	Kruskal-Wallis H Test	Post-Hoc Test
Collected data is too sensitive.	MR	285.26	303.99	212.51	H(2) = 13.528	Y - F p = .007
	Mdn	4 (n=323)	4 (n=194)	3 (n=52)	p = .001	N - F p = .001
The app companies will forward my personal data to third parties.	MR	286.49	292.76	221.19	H(2) = 8.558	Y - F p = .020
	Mdn	4 (n=320)	4 (n=196)	3 (n=49)	p = .014	N - F p = .013
Health insurances will access my data and use it against me.	MR	280.26	292.55	251.21	H(2) = 2.713	-
	Mdn	4 (n=322)	4 (n=193)	3 (n=48)	p = .258	
The app companies will misuse my data.	MR	273.73	300.64	243.96	H(2) = 6.428	N - F
	Mdn	4 (n=318)	4 (n=194)	3 (n=48)	p = .040	p = .074
I have no control over what will happen to my data.	MR	280.19	306.82	230.01	H(2) = 10.022	N - F
	Mdn	4 (n=322)	4 (n=197)	3 (n=50)	p = .007	p = .007
It will be possible to create an exact profile of my movements, habits or preferences.	MR	282.35	299.05	235.90	H(2) = 6.585	N - F
	Mdn	4 (n=322)	4 (n=195)	4 (n=50)	p = .037	p = .032
There will be interference risks from hackers and other unauthorized parties.	MR	284.66	292.13	231.32	H(2) = 6.113	N - F
	Mdn	4 (n=320)	4 (n=194)	3 (n=50)	p = .047	p = .044

8.3.3 Fitness tracking user types by privacy concerns (RQ3)

The final research question concerns identifying and characterizing subgroups of fitness tracking applications' users based on their perceived sensitivity of different data pieces and privacy concerns. The K-means cluster analysis with K1=3 revealed three very distinctive groups of users. For better identification of data privacy concerns, the medians for each cluster and data piece were aggregated into groups of perception as "sensitive" (for medians equaling 4 or 5), "neutral" (median equaling 3) and "not sensitive" (medians equaling 1 or 2), see Table 8.4.

Table 8.4: Results of K-means clustering procedure on perceived data sensitivity, grouped into perception as "not sensitive" (1-2), "neutral" (3) and "sensitive" (4-5). Abbreviations: Blood Pressure (BP), Heart Rate (HR).

	CL1 (n=64)	**CL2 (n=120)**	**CL3 (n=43)**
Sensitive	Real name, Birthday, E-Mail, Contacts/friends, Interest groups, Calories (burned/intake), HR, BP, Sleeping times, BMI, Weight, Menstrual cycle, Step count, GPS, Climbed stairs, Standing hours, Completed workouts, Fitness level or XPs, Trophies or badges, Lost challenges, Won challenges	Birthday, E-Mail, Contacts/friends, Interest groups, HR, BP, Sleeping times, BMI, Weight, Menstrual cycle, GPS	E-Mail, Contacts/friends, GPS
Neutral	Gender	Real name, Calories (burned/intake), Standing hours, Completed workouts, Fitness level or XPs, Trophies or badges, Lost challenges, Won challenges	Real name, Birthday, Interest groups, Menstrual cycle
Not sensitive		Gender, Step Count, Climbed stairs	Gender, Calories (burned/intake), HR, BP, Sleeping times, BMI, Weight, Step count, Climbed stairs, Standing hours, Completed workouts, Fitness level or XPs, Trophies or badges, Lost challenges, Won challenges

The first cluster (CL1, with 64 users) includes users that can be described as rather cautious about data sensitivity, since except for "gender" (perceived as neutral), all remaining data pieces are regarded as sensitive. A more detailed differentiation between "sensitive" and "very sensitive" perception of data pieces can be gathered from Table 8.5. Here, we can see that for CL1, the most sensitive data pieces are "contacts /friends," most of the health-related data pieces, and the GPS location.

The second cluster (CL2, with 120 users) can be described as rather neutral or balanced in the valuation of the data pieces. Here, eleven of the data pieces (personal and health-related information) is perceived as sensitive (however, only "GPS" is valued as "very sensitive" (Table 8.5)). Most of the activity and progress data is perceived as neutral. The "not sensitive" information pieces are gender, step count, and climbed stairs.

Finally, the third cluster (CL3, with 43 users) can be described as rather indifferent or unconcerned about the different data pieces. The only sensitive data seem to be the "e-mail," "contacts/friends," and the "GPS" location (however, none of them are perceived as "very sensitive"). The data pieces "real name," "birthday," "interest groups," and "menstrual cycle" are perceived as neutral, whereas others are seen as "not sensitive."

Table 8.5: Results of K-means clustering procedure on perceived data sensitivity (scale from 1 to 5).

	Data Pieces	**CL1 N=64**	**CL2 N=120**	**CL3 N=43**
Personal data	Real name	4	3	3
	Gender	3	2	2
	Birthday	4	4	3
	E-Mail	4	4	4
	Contacts/Friends	5	4	4
	Interest groups	4	4	3
Health-related data	Calories intake	4	3	2
	Burned calories	4	3	2
	Heart rate	4	4	2
	Blood pressure	5	4	2
	Sleeping times	5	4	2
	BMI	5	4	2
	Weight	5	4	2
	Menstrual cycle	5	4	3
Activity & progress data	Step count	4	2	1
	GPS	5	5	4
	Climbed stairs	4	2	2
	Standing hours	4	3	2
	Workouts	4	3	2
	Fitness level, XPs	4	3	2
	Trophies, badges	4	3	2
	Lost challenges	4	3	2
	Won challenges	4	3	2

In order to detect further differences between the three clusters that could influence the perceived data sensitivity, the cluster membership of each case was saved into a new variable and the Kruskal-Wallis H Test was conducted for these subgroups of fitness tracking applications' users. Several factors, e.g., fitness level or origin, were investigated. Indeed, the Kruskal-Wallis

H Test revealed significant differences in distribution between the three clusters (CL1-CL3) for the fitness or exercise activity (ranging from 1 to 8), $H(2) = 10.628$, $p = .005$; CL1 (Mean Rank = 93.8; Median = 6), CL2 (Mean Rank = 118.20; Median = 6.5) and CL3 (Mean Rank = 132.33; Median = 7). According to the post-hoc test, the significant differences are given between CL1 and CL2 ($p = .039$) and between CL1 and CL3 ($p = .006$).

Further significant differences in distribution between the three clusters are given for the general attitude towards online privacy, namely "I am not concerned about security on the internet, e.g. people finding out what websites I visit or getting to know my real identity" (answered on a 5-point Likert scale), $H(2) = 6.069$, $p = .048$; CL1 (Mean Rank = 99.77; Median = 2), CL2 (Mean Rank = 115.92; Median = 2) and CL3 (Mean Rank = 129.81; Median = 3). There was only one significant difference between CL1 and CL3 ($p = .047$).

The last significant difference in distributions was given for the general opinion on online privacy: "I do not care what companies whose services or applications I use do with my (personal) data" $H(2) = 19.326$, $p < .001$; CL1 (Mean Rank = 89.20; Median = 1), CL2 (Mean Rank = 116.79; Median = 2), CL3 (Mean Rank = 141.12; Median = 2). The significant differences were given between CL1 and CL2 ($p = .010$) and between CL1 and CL3 ($p < .001$).

According to the Kruskal-Wallis H Test, there were no significant differences between the three clusters regarding the everyday activity level, the usage frequency as well as usage duration of the fitness tracking application, and the age of the participants. In order to detect possible cultural differences in cluster membership between participants from the EU and from the USA, the Pearson Chi^2 was calculated. However, there were no significant differences between participants from these two regions.

The first three clusters were estimated based on the users' perceived sensitivity of different data pieces. Another three clusters (CL4-CL6) were calculated based on the data privacy-related concerns regarding fitness tracking applications (Table 8.6). Here, the CL4 (n=104) includes users agreeing with the most concerns. Except for the one: "collected data is too sensitive," they highly agree with all the remaining statements (median equals 5). The next cluster, CL5 (n=63), includes rather unconcerned users. They do not agree with the most statements and are neutral (median equals 3) with concerns about the collected data being too sensitive as well as the statement "it will be possible to create an exact profile of my movements, habits or preferences." Finally, the last cluster, CL6 (n=137), consists of users having slight concerns. They somewhat agree with most of the statements, except for the two about the collected data being too sensitive and the one stating that "health insurances will access my data and use it against me," towards which they have a neutral attitude (median equals 3).

Similar to the first three clusters, the Kruskal-Wallis H Test was conducted for the Clusters CL4-CL6. The results show that there are significant differences in distribution between the clusters for general online privacy concerns, namely the statement "I am not concerned about security on the Internet": $H(2) = 31.151$, $p < .001$; CL4 (Mean Rank = 118.11; Median = 2), CL5 (Mean Rank = 189.06; Median = 3), and CL6 (Mean Rank = 161.80; Median = 2). The post- hoc test revealed significant differences between CL4 and CL5 ($p < .001$) and between CL4 and CL6 ($p < .001$).

There are also significant differences in the agreement with the statement "I do not care what companies whose services or applications I use do with my personal data," $H(2) = 34.248$, $p < .001$; CL4 (Mean Rank = 119.70; Median = 1), CL5 (Mean Rank = 195.15; Median = 2) and CL6 (Mean Rank = 157.78; Median = 2). According to the post-hoc test, the significant differences are given between all clusters: CL4 and CL6 ($p = .001$), CL4 and CL5 ($p < .001$), and CL6 and CL5 ($p = .008$).

The tests revealed no significant differences between the clusters for the everyday activity level, the fitness or exercise level, the usage frequency and usage duration of the fitness tracking application as well as the age of the user. Furthermore, according to Pearson Chi2, there were no significant differences in cluster distributions between users from the EU and the USA.

Table 8.6: Results of K-means clustering procedure on data privacy-related concerns regarding fitness tracking applications (scale from 1 to 5).

Concerns	**CL4 (n=104)**	**CL5 (n=63)**	**CL6 (n=137)**
Collected data is too sensitive.	4	3	3
The app companies will forward my personal data to third parties.	5	2	4
Health insurances will access my data and use it against me.	5	2	3
The app companies will misuse my data.	5	2	4
I have no control over what will happen to my data.	5	2	4
It will be possible to create an exact profile of my movements, habits or preferences.	5	3	4
There will be interference risks from hackers and other unauthorized parties.	5	2	4

8.4 Discussion

How do different groups of participants perceive the sensitivity of various data pieces collected by fitness tracking technologies? And what specific privacy concerns do they have, when thinking about this technology? When comparing current users, former users, and non-users of fitness tracking applications, there are only two significant differences between users and non-users in perception of "personal information"—the sensitivity of "gender" (perceived as neutral or not sensitive) and "interest groups." All other personal data pieces were perceived as at least sensitive by all groups.

More significant differences were given for health- related data. All groups agreed on the sensitivity of information about "menstrual cycle." All remaining information pieces were perceived differently between users and non-users. In general, current users perceive calories ("burned" or "intake") and "heart rate" as neutral, and the remaining data pieces as sensitive. The non-users perceive only "burned calories" as neutral and rest as sensitive. Finally, the former users only perceive information about "BMI," "weight," and "menstrual cycle" as sensitive.

Regarding the activity and progress data, all three groups agree on high sensitivity of "GPS," which confirms the results by Lidynia et al. (2019). Except for "GPS," users and former users perceive all remaining activity and progress data as neutral. Non-users perceive most of the data pieces as neutral, except for "step count" (very sensitive), "fitness level or experience points," and "lost challenges" (rather sensitive). Even though they perceive "lost challenges" as rather sensitive information, their perception of the information about "won challenges" is neutral.

The second research question addressed the data privacy-related concerns about fitness tracking applications. There were no significant differences in distribution between the three groups for the statement "health insurances will access my data and use it against me." In general, the former users seem less concerned about the aspects and see most of them as neutral, except for the concern that "it will be possible to create an exact profile of my movements, habits or preferences," which they slightly agree with. The users and non-users on average agree with all the statements. Here, an interesting question arises, why the former users stopped using these applications or wearables and whether any privacy-related concerns played a role. Since users in this investigation still appear to have some reservations about data privacy, but continue using the fitness tracking technologies, it might not be a key aspect, when making a decision to stop or continue using the technology.

The third research question regarded potential subgroups of fitness tracking applications' users based on their (a) perceived data sensitivity and (b) data privacy-related concerns about fitness tracking applications. The first K-means clustering procedure (K1=3) yield three distinctive subgroups of users: CL1 (concerned users, n=64), CL2 (neutral users, n=120), and CL3 (unconcerned users, n=43). The concerned users indeed perceive all data pieces as (very) sensitive, except for "gender" (neutral). The neutral users are more balanced in their perception, as only "GPS" was perceived by them as "very sensitive," whereas 11 data pieces (personal and health-related information) as "sensitive." They perceive most of the activity and progress data as neutral and information like "gender," "step count," and "climbed stairs" as "not sensitive." Finally, the unconcerned users do not perceive any of the information pieces as "very sensitive," and valued only three data pieces ("e-mail," "contacts/friends," and "GPS") as "sensitive" and four data pieces ("real name," "birthday," "interest groups," and "menstrual cycle") as "neutral." They perceive the remaining information as "not sensitive." The differences between these three clusters are not limited to the perceived data sensitivity.

Subsequent Kruskal-Wallis H Test revealed that the unconcerned users are on average the most active ones (regarding "fitness or exercise" activity), followed by neutral users. It could also mean that users of activity tracking technologies, who are very active, might not fear the "publicity" of the collected data that supports their healthy lifestyle. As one would probably expect, users who are generally doubtful about data privacy online, are also more concerned about the sensitivity of different data pieces. Their perceived sensitivity of data might be this high due to (perceived) lack of safe (data) environment, where personal data is protected from hackers and other misuse, and due to very limited (or non-existent) trust in the companies who have custody of the data. For example, the concerned users tend to disagree more with the statement "I am not concerned about security on the internet" than the unconcerned users (who are rather neutral towards it). Furthermore, the concerned users tend to strongly disagree with the statement "I do not care what companies whose services or applications I use do with my (personal) data," whereas neutral users and unconcerned users only somewhat disagree. Interestingly, there are no significant differences between the three user groups regarding age as well as the usage duration and usage frequency of the fitness tracking application. Finally, there was no significant association between the cluster membership and the origin of the users.

The second clustering procedure (K2=3) involved users' data privacy-related concerns about fitness tracking applications. The identified subgroups include: highly concerned users (CL4, n=104, strongly agreeing with almost all statements), unconcerned users (CL5, n=63, not agreeing with most of the statement or being neutral), and slightly concerned users (CL6, n=137, somewhat agreeing with most of the statements). Further differences between these three subgroups regarded the general online privacy concerns, which were again higher for the cluster with highly concerned users. Interestingly, there were no significant differences between the clusters regarding the usage frequency and usage duration of the fitness tracking application, the age of the user as well as for the everyday activity and the fitness or exercise level. There were also no significant differences in distributions between users from the EU and the USA, indicating a rather similar distribution of data related unconcerns between users from these two regions.

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9 Data Privacy-Related Behavior and Concerns of Activity Tracking Technology Users from Germany and the USA

Ilhan, A., & Fietkiewicz, K. J. (2020). Data privacy-related behavior and concerns of activity tracking technology users from Germany and the USA. *Aslib Journal of Information Management*. https://doi.org/10.1108/AJIM-03-2020-0067 (in press).

Abstract Purpose: *This investigation aims to examine the differences and similarities between activity tracking technology users from two regions (the USA and Germany) in their intended privacy-related behavior. The focus lies on data handling after hypothetical discontinuance of use, data protection and privacy policy seeking, and privacy concerns.* **Design/Methodology/Approach:** *The data was collected through an online survey in 2019. In order to identify significant differences between participants from Germany and the USA, the chi-squared test and the Mann-Whitney U test were applied.* **Findings:** *The intensity of several privacy-related concerns was significantly different between the two groups. The majority of the participants did not inform themselves about the respective data privacy policies or terms and conditions before installing an activity tracking application. The majority of the German participants knew that they could request the deletion of all their collected data. In contrast, only 35% out of 68 participants from the US knew about this option.* **Research limitations/implications:** *This study intends to raise awareness about managing the collected health and fitness data after stopping to use activity tracking technologies. Furthermore, to reduce privacy and security concerns, the involvement of the government, companies, and users is necessary to handle and share data more considerably and in a sustainable way.* **Originality/Value:** *This study sheds light on users of activity tracking technologies from a broad perspective (here, participants from the USA and Germany). It incorporates not only concerns and the privacy paradox but (intended) user behavior, including seeking information on data protection and privacy policy and handling data after hypothetical discontinuance of use of the technology.*

9.1 Introduction

Data privacy has become one of the most prominent concerns of our modern times within the realm of technology. With the upcoming activity tracking technologies, not only personal but also health and fitness data are collected and stored in databases, out of reach, and out of control for the users. According to IDC (2019), "the worldwide market for wearable devices grew 31.4% [...] (4Q18)." Activity tracking technologies enable users to collect a variety of different data, e.g., steps, burned calories, sleep duration, or heart rate. This allows the support of a healthy lifestyle or enables users to better control their physical activity. Activity trackers (e.g., Fitbit, Garmin), smartwatches (e.g., Apple Watch, Samsung Gear), and mobile applications (e.g., Runkeeper or Strava) are defined as activity tracking technologies. While the hype about activity and fitness tracking wearables and mobile applications is getting more omnipresent, the management of the data collected by users should be more scrutinized. According to Dinev and Hart (2006), privacy concerns are defined as the threat that users' information is revealed without authorization. However, the complexity of this issue goes way beyond that. Vitak, Liao, Kumar, Zimmer, and Kritikos (2018) stress that most of the participants in their study did not know how the wearable technology companies store their data (i.e., time of retention and location of storage apart from the device itself). Moreover, users of activity and fitness wearables perceive some of the personal, health, and fitness data pieces as sensitive (Fietkiewicz & Ilhan, 2020a; Lidynia, Brauner, & Ziefle, 2018). As convenient and easy the tracking and collection of health and fitness data work for users, possible consequences (i.e., misuse of sensitive data, unauthorized access by third parties) were not thoroughly investigated. In particular, the increasing pace of technological development is accompanied by the uncertainty of where it will lead and how all the collected data could be exploited in the future (Fietkiewicz & Lins, 2016).

Physical activity and fitness tracking are gaining popularity not only among consumers but also in scientific research. When looking into research on activity tracking technologies, most studies focus on the accuracy of the trackers (see, e.g., Evenson, Goto, & Furberg, 2015; Rosenberger, Buman, Haskell, McConnell, & Carstensen, 2016). Usability, engagement, adoption, and acceptance were investigated as well (see, e.g., Feng, Li, & Agosto, 2017; Fritz, Huang, Murphy, & Zimmermann, 2014; Gouveia, Karapanos, & Hassenzahl, 2015; Ilhan & Henkel, 2018; Lyall & Robards, 2018; Nelson, Verhagen, & Noordzij, 2016; Rooksby, Rost, Morrison, & Chalmers, 2014). The number of studies on activity tracking technologies (applications and wearables) increased over the last years, which was confirmed by the systematic literature review (2013-2017) conducted by Shin et al. (2019). Based on a topic modeling analysis, Shin et al. (2019) were able to detect six thematic clusters. The "privacy" cluster is one of them. Interestingly, out of 463 studies considered, only 6% (29 articles) investigated the topic of privacy. As reported by Fietkiewicz and Henkel (2018), more extensive user-oriented research that goes beyond users' privacy preferences is needed in the context of activity and fitness tracking and data privacy. The legal differences between the EU (and Germany in particular) and the USA seem to prevail after the General Data Protection Regulation (GDPR) came into force in May 2018. Due to these differences, the transatlantic data transfer remains a challenge, and recently (as of July 2020) another agreement between the EU and the USA, the EU-US Privacy Shield (which replaced the voided Safe Harbor agreement), was declared as invalid by the European Court of Justice (CJEU, 2020). Fietkiewicz and Ilhan (2020b) revealed that most of the participants in their survey did not believe that GDPR will change the data privacy environment in the EU for the better. More recent evidence (Paul, Scheibe, & Nilakanta, 2020) suggests that the perceived privacy risks (e.g., unauthorized access to collected data) and privacy concerns (e.g., misuse) show an interdependence. When privacy risks are perceived as high, more concerns can be identified. Furthermore, they revealed that

GDPR helped to reduce some of the privacy concerns (Paul et al., 2020).

A neglected area in the field of activity tracking technologies is user-centered data privacy research and the mediating effect of culture. Previous work mainly focused on the technological perspective (e.g., encryption of health-related data, see (Abbas & Khan, 2014; Fernández-Alemán, Señor, Lozoya, P. Á. O., & Toval, 2013)). When we look at culture or origin (regardless of the legal framework) as a factor influencing the use of digital media or data privacy-related behavior and concerns, several studies confirmed its significant impact. Y. Li, Wang, Lin, and Hajli (2018) detected important cultural differences regarding users' intentions to seek and share health information on social media (the study focused on China and Italy). There also appear to be moderating effects of cultural difference and socioeconomic status when it comes to motivational factors (uses and gratifications theory) and the continuance intention of social media. This was shown by Hsu, Tien, Lin, and Chang (2015) in a study investigating users from Australia, Austria, Japan, Taiwan, and the USA. Other studies showed cross-cultural differences in using social media regarding information seeking and privacy (Fietkiewicz, Lins, & Budree, 2018) or in social media disclosure of mental illness (Choudhury, Sharma, Logar, Eekhout, & Nielsen, 2017).

Other studies focused on privacy concerns and trust in particular, e.g., users' privacy concerns on social networking sites in the USA, China, and India (Wang, Norice, & Cranor, 2011). According to Wang et al. (2011), US-American users were most concerned about privacy during the use of Social Networking Sites (SNSs), followed by Chinese and Indian users. However, participants from the US also "exhibited the lowest level of desire to restrict the visibility of their SNS information to certain people (e.g., co-workers)" (Wang et al., 2011, p. 146). Tsoi and Chen (2011) revealed significant differences between users from Hong Kong and France regarding privacy concerns, trust, and motives for using a SNS (Facebook). Pentina, Zhang, Bata, and Chen (2016) looked at perceived privacy concerns and perceived benefits during the adoption of private-information sensitive mobile applications in the USA and China. Interestingly, for users from both countries, the perceived privacy concerns did not play a role in the adoption (or intention of using) of the application. These results confirm the so-called privacy paradox (Hargittai & Marwick, 2016; Norberg, Horne, & Horne, 2007), meaning that "risk perception does not have a strong enough influence on actual risk-avoiding behavior in the presence of strong positive perceptions of obtained benefits" (Pentina et al., 2016, p. 417). Trepte and Masur (2016) investigated the subjective privacy literacy (level of participants' knowledge regarding the ability to use privacy settings) of users from the USA, the UK, Germany, the Netherlands, and China. Here, the US-American participants rated their knowledge about privacy settings higher than the participants from other countries, whereas German participants were more likely to restrict access to their profile information (e.g., the visibility of contact details, birthday, age, or relationship status). While "more than one third of all participants did not know if their profile could be found by search engines [. . .], half of the German subsample reported using the privacy setting to restrict their profile and render it unsearchable by search engines" (Trepte & Masur, 2016, p. 33). Miltgen and Peyrat-Guillard (2014) studied cultural and generational influences on privacy concerns in several European countries (grouped geographically into north, south, east, and west). There appear to be significant differences between northern and southern countries regarding the importance of responsibility (as opposed to trust) as well as between south and east regarding the perception of disclosure being a “choice” (in the south) and being “forced” (in the east) (Miltgen & Peyrat-Guillard, 2014). Krasnova, Veltri, and Günther (2012) looked at differences between the USA and Germany regarding privacy concerns, trust in the provider and the members, and showed that culture moderates the impact of privacy concerns and trusting beliefs. A higher level of individualism in a culture “facilitates the development of trusting beliefs, thereby stimulating users to reveal information,” whereas lower levels of “uncertainty avoidance” lead the users to “ignore their privacy concerns, even when they have ones” (Krasnova et al., 2012, p. 134).

Proceeding from this short insight into investigations of culture-dependent differences in behavior and privacy concerns within the digital environment, this paper seeks to address users’ data privacy-related awareness, behavior, and concerns and provides a more holistic view on this issue within the realm of activity tracking technology. To understand if and how the culture plays a role in privacy-related user behavior, activity tracking technology users from two regions, Germany and the USA, were investigated.

This is a user-centered study. However, are users the only ones responsible for data protection? According to Lessig (2006), the code is the law. In this case, the code is the software itself. The difference between the Internet ’net’ and the software is important. While the Internet is ”neutral about the data and ignorant about the user,” the code as software (application) can be changed (by the coders) (Lessig, 2000). Without regulation, the code might either ensure suitable data privacy or lack it. This also holds for activity tracking technologies. Here, the governmental regulation (legislation, e.g., the GDPR) as well as appropriate self-regulation of the providers (e.g., privacy policies) and complying coding and system design to support the users in sustainable and secure data behavior are needed. Finally, the users themselves need to take responsibility for their data. This view of shared responsibility is also considered in the present study.

The users can contribute to the privacy and protection of their data as long as they reached a certain level of information literacy and have the respective awareness (and willingness) to do so. When it comes to data privacy, these end-users need to be supported by appropriate legislative infrastructure and treated fairly by the companies of wearables. In their study, Schneegass, Poguntke, and Machulla (2019) showed that there is a lack of understanding of the correlation between the sensors implemented in activity tracking technologies and the information derived from them. They state that data requests should be based on derived information instead of all data collected by the sensor. Schneegass et al. (2019, p. 5) mention that “users do not seem to be fully aware of the type of information that can be derived from different sensors.” Zimmer, Kumar, Vitak, Liao, and Kritikos (2020) point out that some participants agree that they should be worried about the data privacy of their collected health and personal information. They stress that some participants also reported that after the first time changing privacy settings, “they had not checked or adjusted the settings since then” (Zimmer et al., 2020, p. 1030). Furthermore, the possibility to take action regarding managing privacy is not homogenous and evident at all. Participants explained that they have to know that some settings are only accessible through the website instead of the mobile application (Zimmer et al., 2020). Perceived privacy concerns depend on the sensitivity of the information. Furthermore, it remains the companies' task to provide user-friendly privacy and data policies as well as a suitable system design.

In a study by Pingo and Narayan (2018), participants complained that the privacy and data policies are regularly too long and that they have no real choice not to accept it if they would like to use the activity tracking technologies. An in-depth look into one of the popular activity and fitness tracking applications suggests a positive change toward giving the consumers more control over their data, possibly initiated by the GDPR. For example, in the Samsung Health application, the users can easily request the deletion of all their data collected through the application. However, the question arises whether the users of activity and fitness tracking applications and wearables are aware of this function. Besides, how would users act to protect their data if they were about to stop using the activity tracking technologies? Are there any differences between users from Germany and the USA since GDPR is effective in the EU and promises stronger data privacy for EU consumers? Indeed, the Europeans are making use of their rights provided with GDPR and are becoming more aware of the new claims (European Commission, 2019). These considerations lead us to the following research questions (RQs):

RQ1a: Are there significant differences between users from Germany and the USA regarding their awareness of the possibility to request the deletion of all data collected by an activity and fitness tracking application and wearable?
RQ1b: Are there significant differences between users from Germany and the USA regarding their potential behavior after stopping to use an activity and fitness tracking application and wearable?

The option to request the deletion of data is one of several possibilities for users wanting to handle their data more responsibly. Nevertheless, Pingo and Narayan (2018) mention that data privacy protection is not concluded by simply offering privacy settings. "The privacy settings feature requires effort and some form of privacy literacy to understand how they function, in order to meaningfully use them to safeguard the informational privacy of oneself and others" (Pingo & Narayan, 2018, p. 250). Another crucial aspect to consider is the privacy policy of activity tracking technologies' companies. Even if privacy policies are informative, they can also be overloaded with information and utterly overwhelming. From an information science perspective, Case and Given (2016) explain that the perceived feeling of information overload leads to an information avoidance behavior, which helps to deal with those circumstances. Too much information and long privacy policies lead to a situation where people either do not read them completely or do not read them at all, even though they decide to use an application (Pingo & Narayan, 2018). Considering that the consumers rarely read privacy policies, the question arises whether activity and fitness tracking users seek any information about what happens with their personal and health data and, if so, which sources they prefer.

RQ2: Do users of activity and fitness tracking technologies from Germany and the USA inform themselves differently about the company's data privacy policies?

Activity or health data might give power and control to both the consumer who can monitor, analyze, and improve his or her fitness or physique and to other (unauthorized) third parties. These risks of data misuse or third-party interference might bring about concerns among users of activity and fitness tracking technologies. Even though users are aware of these risks, they start or continue to use the technologies (this is the so-called privacy paradox). As Norberg et al. (2007, p. 101) stress, it is not a surprise "that people are willing to trade personal information for perceived benefits." To monitor the own health and fitness level can be both a boon and bane of today's digitalization regarding privacy and the corresponding threats. According to H. Li, Wu, Gao, and Shi (2016), consumers' attitudes and their actual behavior diverge.

In previous research, several privacy concerns have been studied in more detail. For example, Lidynia, Schomakers, and Ziefle (2019) investigated the perceived privacy and data security barriers to the adoption of fitness applications and wearables by 166 German users and non-users. The non-users were somewhat more concerned than the users of fitness tracking applications about aspects as data misuse, forwarding data to third parties, or not having any control over their data (Lidynia et al., 2019). However, when considering the results of user-centered research by Nelson et al. (2016) on data privacy, they are not concurrent with results by Lidynia et al. (2019), which might underline the diversity of perceived data privacy and protection. Nelson et al. (2016) investigated activity trackers in the context of privacy protection. The participants of their study tended to agree that they are not concerned about the unauthorized use of their personal information or the unwanted sharing with third parties. Schomakers, Lidynia, and Ziefle (2019) found that the adoption of activity tracking technologies depends on privacy concerns. Concerns such as data sensitivity and trust in data protections are identified as barriers to the use of activity tracking technologies. They stress that "the more sensitive users perceive the collected data to be, the higher their privacy concerns" (Schomakers et al., 2019, p. 310). They suggest that different actions need to be taken, as the privacy concerns and the sensitivity of data are perceived differently.

Ilhan and Henkel (2018) also reported that users of activity trackers generally trust the provider to refrain from abusing their data in any way. Users in the USA are somewhat more convinced about this than users in Germany (Ilhan & Henkel, 2018). Pingo and Narayan (2018) showed that sharing information collected by fitness trackers with health insurance funds is perceived as beneficial (e.g., reducing costs) and uncomfortable (e.g., it can be used against the users). While users might feel uncomfortable, Henkel, Heck, and Göretz (2018) found that for some health insurance funds, this is not necessary. Four German health insurance funds (AOK Nordost, AOK Plus, BARMER, and Techniker Krankenkasse) "clearly state that only the bonus points for the processing of the bonus program and no actual fitness data is collected and stored" (Henkel et al., 2018, p. 39). Ilhan and Henkel (2018) explained that their participants tended to agree they should be eligible for financial support if they share their fitness activity data with a health insurance company. This behavior is not necessarily generalizable to all users of activity tracking technologies. However, even if they use the technology (and some willingly share information to receive benefits from health insurers), they still might have concerns about their data. To better understand the concerns of users in Germany and the USA, we formulate the following research question:

RQ3: What are the differences between German and US-American users' data privacy concerns about activity and fitness tracking technologies?

We aim at expanding the research area of data privacy and activity tracking technologies with an extensive user-centered study to better understand the privacy-related information behavior in this context. Information behavior is one of the core aspects of information science. Regarding the privacy-related settings and the information-seeking behavior, the concept of information literacy comes to the fore. McKinney, Cox, and Sbaffi (2019, p. 11) explain that aspects such as "developing awareness of when and how to share their data, and developing and understanding of who has access to their data and the potential for sharing and reuse without their explicit consent" are assigned to information literacy.

Hagen (2017) also mentions digital literacy, which impacts the user's privacy-related information behavior. According to Bawden (2001), digital literacy is used synonymously with digital information literacy. Therefore, this could imply that digital literacy (or digital information literacy) includes digital privacy literacy. Hagen (2017) investigated to what extent digital literacy can decrease privacy concerns and support responsible behavior (information disclosure) in terms of data privacy. Hagen (2017) mentioned that the selection of privacy settings does not reflect users' privacy concerns. Non-modified privacy settings by the users do not necessarily indicate that they do not care about their data privacy, but the reason for such behavior could be the level of digital literacy. According to Hagen (2017, p. 1), "[o]ne reason for this paradoxical behavior is users' low digital literacy; a limited knowledge about what technologies can actually do may create a nonchalant attitude about privacy settings." Furthermore, Hagen (2017, p. 1) mentioned that "companies collecting personal information have an advantage over consumers, reinforcing low digital literacy and impacting their customers' inability to make informed decisions regarding the transmission of their personal information." Additionally, Hagen (2017) explains that even if companies are trying to communicate their policies transparently, a gap between the meaning of the information and the users' understanding might still exist.

McKinney et al. (2019) also support the notion that digital literacy (information literacy) is an important aspect when considering privacy-related information behavior. They explain that topics concerning privacy and personal data are aspects of information literacy as well. "The extent to which people are aware of issues to do with the privacy of their personal data held in mobile apps or shared online is also an aspect of information literacy" (McKinney et al., 2019, p. 3). Further, even if the authors did not investigate activity tracking technologies (such as wearables), the topic of activity and health tracking through other tools (such as mobile applications) concerns the same sensitive data. Therefore, the conclusion by McKinney et al. (2019, p. 12) that "[e]ffective and safe use of tracking thus depends on information literacy" is also applicable to wearable activity-tracking technology. McKinney et al. (2019, p. 13) also state that "a greater area of concern is around people's lack of awareness of risks around platform use of data and continuity of access. This implies the need for much better public awareness around data ownership, and simplified privacy statements might assist in this."

Further, as concluded by Wissinger (2017, p. 380), "privacy literacy definitions focus on the understanding of the responsibilities and risks associated with sharing information online [...]." Therefore, this investigation analyzes to what extent users agree to take responsibility for their data and their awareness about sustainable data privacy management (e.g., deleting data). This is getting more and more important when considering the omnipresent digitization. Vast amounts of new data are produced and collected every second. The risk of users accepting the threats (due to privacy paradox and privacy calculus theory (PCT)) for the possible benefits still exists. The study by Cox, McKinney, and Goodale (2017, p. 194) revealed that "[m]any were aware of data privacy issues, but some felt since the tools were free, the use of their data was a fair exchange."

Fox (2020) investigated users' privacy-related behavior within the healthcare setting and the everyday usage, and similarly mentioned that an important aspect is the privacy paradox and the PCT. The PCT describes the observation that privacy concerns are tolerated and accepted if the benefits overweight them (Culnan, 1993). Furthermore, Fox (2019) showed that even if users had privacy concerns, they did not stop using mobile health applications in general but looked for other mobile health applications that required less disclosure of sensitive data. The results showed that it is important not only to be aware of how and to what extent data are being collected but also to gain actual control over their own data. "[S]ome noted their only control was in abstaining from use or withholding/falsifying data" (Fox, 2020, p. 1026).

According to Fox (2020), health information privacy concerns impact users' adoption and acceptance of mobile health technologies and their usage behavior. Fox (2020) emphasized that even if users put the benefits over privacy concerns (privacy calculus), this behavior is overall influenced by the extent of their privacy knowledge and self-judgment. Therefore, perceived benefits could be "biased by lack of privacy knowledge and skewed self-perception, and influence not only adoption decisions, but decisions regarding what technology to use, how to use it, and whether or not to continue use" (Fox, 2020, p. 1026).

According to Cilliers (2020), it is important to support users of wearables to fully understand data privacy and security risks. About 50% of the participants are not familiar with how their data is protected and how the data is transmitted and stored (Cilliers, 2020). Furthermore, about 50% of the participants did not know "who to contact if [they] suspect an information security incident" (p. 154). Furthermore, the study by Cilliers (2020) outlined that "two-thirds of the participants did not know what types of health information were being stored or transmitted by their wearable devices" (Cilliers, 2020, p. 154). Especially after such incidents as the MyFitnessPal app data breach in 2018 (The Guardian, 2018), users should be aware of the kind of data saved by the app and possibly vulnerable.

Only a few researchers have addressed the USA and Germany's different legislative backgrounds. This neglected area might influence the mindset and behavior of activity tracking technology users. It remains unclear if users in Germany seem to feel more protected due to a stricter and more consumer-friendly legal framework. To answer the stated research questions, this investigation focuses on current users of at least one activity and fitness application and activity and fitness tracking wearable, who are either from Germany (N=121) or the USA

(N=68). In the following section, a detailed description of the applied methodology is provided.

9.2 Method

9.2.1 Online Questionnaire

The online survey conducted included different blocks of questions, some of which were not privacy-related (e.g., socio-demographic questions, general activity and fitness level, use of activity tracking applications). The online survey was available in English, German, and Polish (due to the available language-skills of the involved authors). This article focuses on privacy-related aspects of activity tracking technology users from Germany and the USA. The broader survey developed in 2019 included non-users, former users, and users from other regions as well (Fietkiewicz & Ilhan, 2020a, 2020b). In this article, these study participants, as well as other questions not related to privacy, will not be considered.

Data Handling after Hypothetical Discontinuance of Usage. In order to estimate users' information management behavior, the potential handling of data after hypothetically discontinuing to use the fitness tracking applications was investigated. In particular, the awareness of the possibility to request the deletion of data collected by the fitness tracking technologies and the decision on how to act after stopping to use an application were studied. These aspects were addressed with two questions: Did you know that you can request the deletion of all data that was collected through the activity tracking application? And If you were about to stop using the activity tracking application, how would you deactivate your account? The answer possibilities (multiple-choice) for the latter included: I would just stop using the application, I would just delete the application, I would deactivate my account, and I would request deletion of all collected data.

Data Policy Seeking Behavior. A further aspect of users' information-seeking behavior is the interest in data policy of the fitness tracking companies. Therefore, a multiple-choice question Did you inform yourself about the data policy of the fitness tracking applications? was added. The answers included: I have read their Data Privacy Policy, I have read their Terms and Conditions, I researched their reputation on handling consumer data on the Internet, and the option I did none of the above.

Data Privacy Concerns Regarding Fitness Tracking Applications. To examine the existence of the privacy paradox (i.e., usage of the service or technology notwithstanding the prevalent privacy concerns) in this area, seven statements (S1-S7) about users' concerns were formulated. The statements could be valued on a 5-point Likert scale (from '1—Strongly Disagree' to '5—Strongly Agree'). The participants also had the possibility to choose the I don't know option. Five of the seven items were adopted from Lidynia et al. (2019). The other two items were added based on the research about the interference of health insurance funds and other third parties (e.g., Henkel et al., 2018; Lehto & Lehto, 2017; Pingo & Narayan, 2018).

9.2.2 Pretest and Distribution

The survey was pretested by six participants (from Germany, Poland, and the USA). Three of these six participants were males, and three were females. Pretesting the survey led to minor modifications in language, formulating statements more objectively, clarifying any ambiguities, adding open questions for further comments, and making the survey more user-friendly by different positioning and segmentation of the questions.

The online survey was non-probabilistically distributed (convenience sampling) from February 26, 2019, until May 28, 2019. It was disseminated through different social media channels, both private profile and social media groups (e.g., Facebook groups, Reddit, Twitter, Xing (a German business networking platform)), scientific communities (Association for Information Science and Technology), survey portals (SurveyCircle, Survey Tandem), mailing lists, and private instant messaging services (e.g., WhatsApp).

9.2.3 Data Preparation and Sample

The collected data were cleaned of incomplete answers and answers of the participants who pretested the survey and recoded with the Syntax of IBM SPSS Statistics 26. The answer possibilities on the Likert scale were not interval scaled and not normally distributed. Therefore, the data will be handled as ordinal. I don't know answers were coded as missing values and excluded from the analysis to not distort the results. To identify significant differences between users from Germany and the USA, the chi-squared test (Pearson Chi-Square) $\chi 2$ (between dichotomous, categorical variables) as well as the Mann-Whitney U test (via SPSS Statistics Legacy Dialogs) for group variables (Germany and the USA) and ordinal data, were applied. For the chi-square test, the strength of association Phi (φ) and degrees of freedom (df), here 1, were calculated in order to measure whether the effect size of the association is small (0.10), medium (0.30), or large (0.50) (Cohen, 1988). For the Mann-Whitney U test, the mean ranks were calculated. The following significance levels were reported: $p - value \leq 0.05$*, $p - value \leq 0.01$**, $p - value \leq 0.001$***.

The sample here includes 189 participants (from Germany and the USA) who currently use a fitness application (e.g., Apple Health, Apple Activity, Fitbit) and an activity tracker or a smartwatch (e.g., Fitbit, Apple Watch). About 44% of the 189 participants are male, 55% are female, and about 1% indicated "other" gender. About 64% of the 189 users are from Germany and 36% from the USA.

9.3 Results

9.3.1 Potential Data Handling after Hypothetical Discontinuance of Usage

The first two research questions (RQ1a and RQ1b) concern the hypothetical user behavior (intention) after hypothetically discontinuing to use the activity tracking technology. First (RQ1a), are there significant differences between users from Germany and the USA regarding their awareness of the possibility to request the deletion of all data collected by an activity and fitness tracking application?

Sixty-four out of 121 German participants (53%) and 24 out of 68 US-American participants (35%) were aware of this option. There was a statistically significant association between the users' origin (Germany or USA) and their awareness of being able to request the deletion of all collected data ($\chi 2(1) = 5.419$, $p \leq 0.05$*), however, with only a small effect size of the association ($\varphi = -.169$, $p \leq 0.05$*).

Second (RQ1b), are there significant differences between users from Germany and the USA regarding their potential behavior after stopping to use an activity and fitness tracking application? The users from Germany would be more likely just to stop using the application or delete it from the smartphone than users from the USA. Users from the USA would be more likely to request the deletion of all collected data. They also tend somewhat more to the deactivation of the account (Figure 9.1). However, some participants remain skeptical about the possibility to request the deletion of all collected data. One user would request the removal of all collected data and deactivate the account if s/he stopped using the application. Nevertheless, s/he commented that "[a]lthough an account can be deactivated and a request be made to delete all data, there is no guarantee that data is truly deleted. That is because there are stored back-ups everywhere. And there is no guarantee that stored/backed-up data isn't being hacked" (participant x_1).

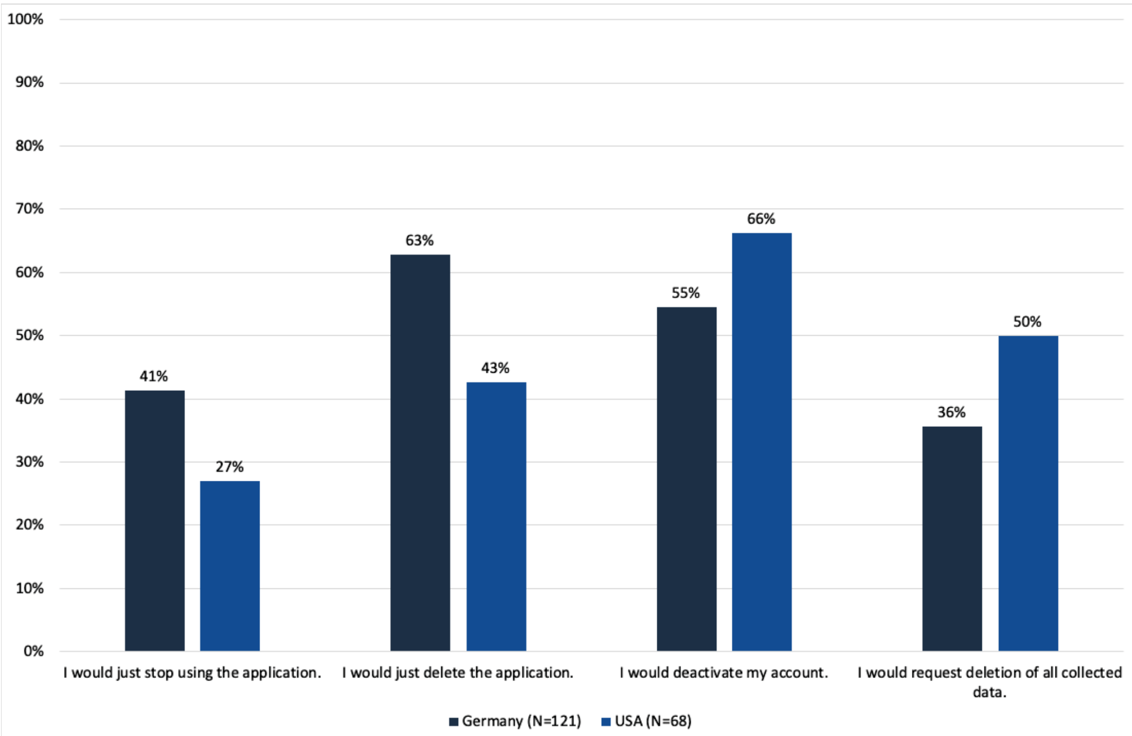

Figure 9.1: Intended data handling in case of hypothetical discontinuance of usage of fitness tracking application

A chi-square test for association was conducted for the users' origin (Germany and the USA) and the probable action of just stopping to use the application. There was a statistically significant association between the users' origin and their information management behavior just to stop using the application ($\chi2(1) = 4.169$, $p \leq 0.05$*) with a small effect size of the association ($\varphi = -.149$, $p \leq 0.05$*). Furthermore, there is a statistically significant association between the decision just to delete the application and users' origin ($\chi2(1) = 7.168$, $p \leq 0.01$**). Again, the effect size of the association was only small ($\varphi = -.195$, $p \leq 0.01$**). There was no significant difference (p> 0.05) between users from Germany and the USA regarding the option of deactivating the account and requesting the deletion of all collected data.

9.3.2 Data Policy Seeking Behavior

The next research question concerned users' information (here, data protection and privacy policy) seeking behavior (RQ2). Do users of activity and fitness tracking technologies from Germany and the USA inform themselves differently about the company's data privacy policies? Figure 9.2 shows that less than half of the German participants read the Data Privacy Policies (31% out of 121 German users), Terms and Conditions (22% out of 121 German users), and Researched companies' reputation on handling consumer data (22% out of 121 German users). Interestingly, more than one-third of the participants from the USA (38% out of 68 participants) researched the company's reputation for handling consumer data on the Internet. Nevertheless, even though 38% of the USA users did actively seek this information, 41% did none of the listed information-seeking behavior. Users from the USA were more likely to read the terms and conditions (31%) or to search for information online (38%) than the German participants.

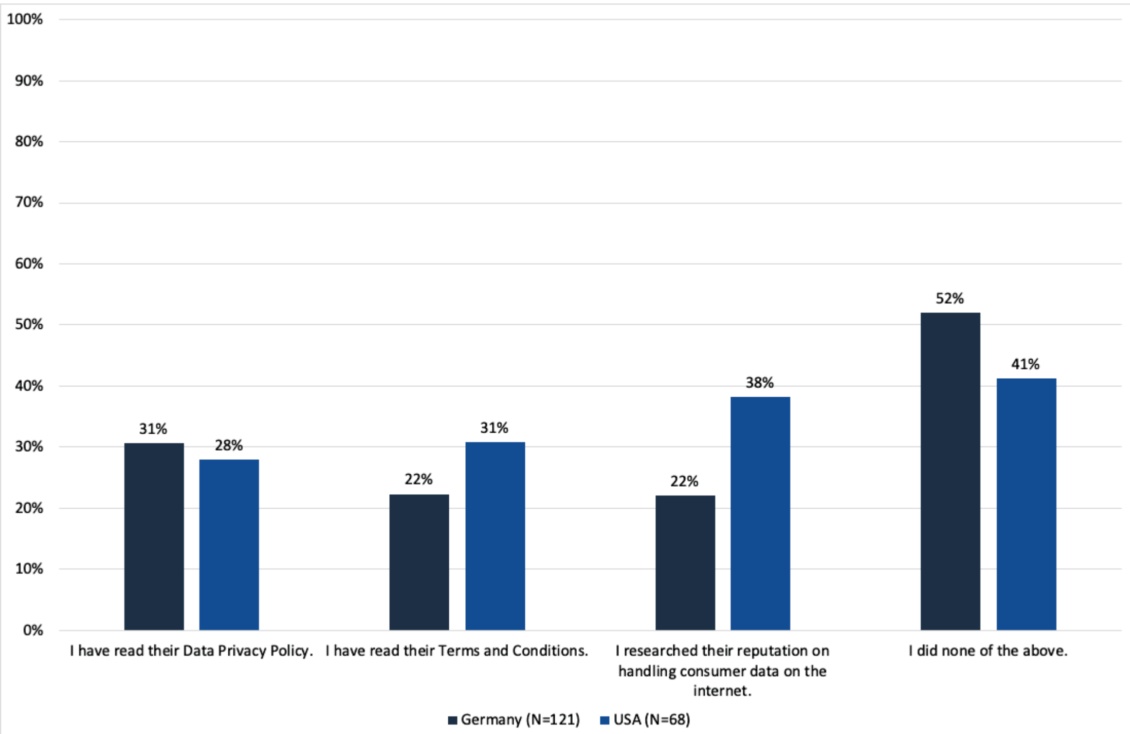

Figure 9.2: Information-seeking behavior considering data policy-related information

A chi-square test for association between the users' origin (Germany and USA) and the data policy-related information-seeking behavior was conducted. There was only one statistically significant association for the action I researched their reputation on handling consumer data on the Internet ($\chi 2(1) = 6.123$, $p \leq 0.05$*). Even though the association is significant, it has only a small effect size ($\varphi = .180$, $p \leq 0.05$*).

9.3.3 Data Privacy Concerns Regarding Activity Tracking Technology

The final question addresses the privacy-related concerns about activity tracking technology (RQ3). What are the differences between data privacy concerns about activity and fitness tracking technologies of users in Germany and the USA? Indeed, the users seem to have some misgivings (Figure 9.3). Interestingly, even though the medians for users from Germany and the USA are at the same level (median 4 – 'Agree') with the exception of one concern (S1), the respective box plots exhibit very different distributions.

As Figure 9.3 shows, around 75% of the answers by participants from the USA tend to "strongly agree" and "agree" that the app companies will forward their personal data to third parties (S2), that they have no control over what will happen to their data (S5), and that it will be possible to create an exact profile of their movements, habits and/or preferences (S6). Except for the statement (S6), it will be possible to create an exact profile of my movements, habits and/or preferences, none of the statements received such a high agreement from the German participants. As for the German participants, around 75% of the answers for the statement S2 varied between neutrality and strong agreement (5), whereas around 50% of the answers for the statement S5 between neutrality and agreement (4).

For almost all statements, the median values for both user groups, from the USA and Germany, equal 4 (indicating an agreement). There is one exception, as the German participants agree (median equals 4) that the collected data is too sensitive (S1) more than participants from the USA, who are neutral about it (median equals 3). Also, for the German participants, the interquartile range equals only 1, indicating a rather strong agreement among the participants about this statement.

As for the two statements, health insurances will access my data and use it against me (S3), and there will be interference risks from hackers and other unauthorized parties (S7), 75% of the answers by US participants vary between neutral (3) and strong agreement (5). However, the remaining 25% of the answers range between strong disagreement (1) and neutral response (3), indicating a rather diversified opinion. As for the German participants, 50% of the answers to the statement (S7) lies between the Likert values 3 and 4.5, with all answers reaching between 1 and 5, which also indicates a low level of consistency in the German users' perception about interference risks from hackers and other unauthorized parties. As for the agreement about the role of health insurances, the answers by German participants showed even less agreement, as they ranged from 1 to 5 (50% of the answers being between 2 "disagreement" and 4 "agreement"), with an interquartile range of 2.

A Mann-Whitney U test was run to determine if there were statistically significant differences in the level of agreement with privacy concerns between participants from Germany and the USA.

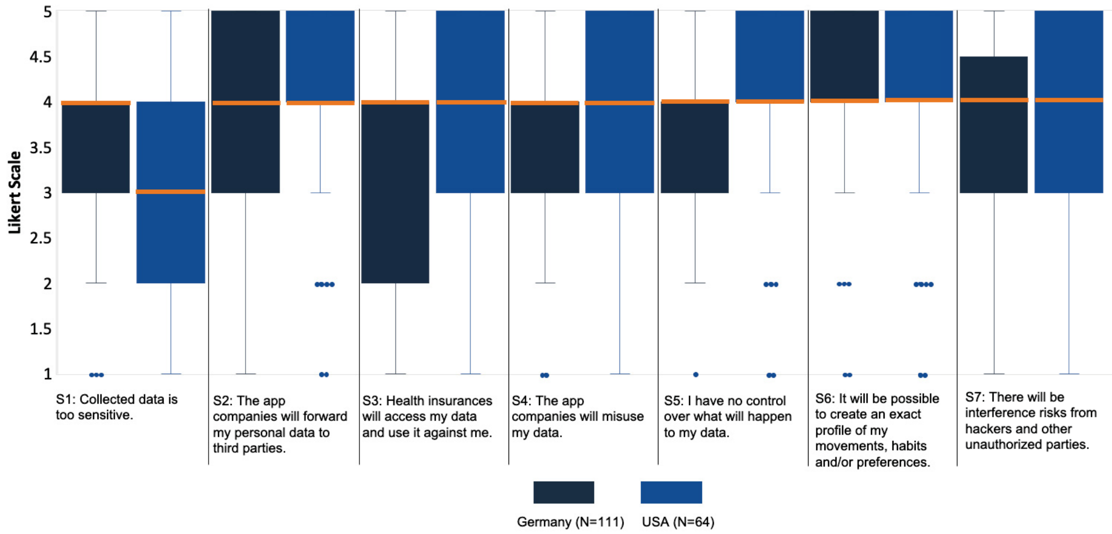

Figure 9.3: Privacy concerns of the German and the US-American activity tracking technology users (1–'Strongly Disagree' – 5–'Strongly Agree'); Excluded cases listwise (missing values)

There was no statistically significant difference in the distribution of agreement considering S1, S2, S6, and S7. The differences between the two groups for the remaining statements (S3, S4, and S5) were statistically significant.
The difference in the distributions of the level of agreement for participants from Germany and the USA regarding the concern that health insurances will access my data and use it against me (S3) was significant (U = 2761.500, z = - 2.531, $p \leq 0.05$*). The agreement values for participants from Germany (Mean Rank = 80.88) are lower than for participants from the USA (Mean Rank = 100.35).

The levels of agreement regarding the concern that app companies will misuse my data (S4) are again significantly higher (U = 2768.500, z = - 2.533, $p \leq 0.05$*) for participants from the USA (Mean Rank = 100.24) than for participants from Germany (Mean Rank = 80.94). Considering the concern I have no control over what will happen to my data (S5), the agreement is again significantly higher (U = 2506.000, z = - 3.367, $p \leq 0.001$***) for participants from the USA (Mean Rank = 104.34) than for participants from Germany (Mean Rank = 78.58).

9.4 Discussion

9.4.1 Awareness of the possibility to request deletion of all collected data (RQ1a) and Potential Data Handling after Hypothetical Discontinuance of Usage (RQ1b)

German participants' awareness of the opportunity to delete all collected data is almost balanced, as 64% of 121 participants from Germany were aware of it. In contrast, 35% of 68 participants from the USA knew about it. The deletion of all collected data can be requested even if a user continues to use the app. Regarding the statement of one participant, requesting the deletion of data is no guarantee because there might still be data stored in the cloud. This indicates that legal regulations are not enough for users to gain more trust. Some of the participants still doubt the effectiveness of legal regulations and mistrust the companies. This might be one of the reasons for lack of interest in or search for such deletion options.

Interestingly, even if only 35% of the participants from the USA knew that they could request the deletion of all collected data, their willingness to request the deletion is higher than for German participants. Considerably different culture-dependent motives might influence what to do after stopping to use a tracking application. As Tsoi and Chen (2011) already found, there exist different privacy-related preferences by users from different countries (here, Hong Kong, and France) when using a SNS. Future studies need to focus more on the theoretical aspects of how culture can influence those decisions and preferences and why 36% of the surveyed German users and 50% of the US-American users would request the deletion of data after opting-out from using the activity tracking application. Interestingly, even though the majority of users from the USA did not know that this is a possibility, they would take advantage of it in the future. This shows that the gained awareness about privacy-related features might encourage users to take responsibility and behave in a more sustainable way when it comes to data management. As Zimmer et al. (2020) also explain, users need to know where to find certain settings and how they are applicable. Some of the participants in our study learned about this feature while participating in the survey. A self-motivated decision to seek such information within the activity and fitness applications would require effort and time.

While users from Germany are more likely to stop using the application (41%) or just delete it (63%), users from the USA tend to the possibility to deactivate the account (66%). This somehow contradicts the results of Trepte and Masur (2016), whose investigation in the context of SNSs showed that US-American users rated their knowledge about privacy settings significantly higher, whereas the German participants were more likely to actively manage their data (e.g., by restricting access to their profile information or making it unsearchable by search engines). This discrepancy indicates that the data management behavior might differ between different technologies (SNS vs. activity tracking technology), between different stages of usage (data management during engagement with the application vs. after usage discontinuance), or it occurred due to differences in data sampling in these two studies. Hence, there might be further mediating factors despite culture that influence the behavior, e.g., age of the participants (Miltgen & Peyrat-Guillard, 2014). Furthermore, the aspect of how long those activity tracking technologies have already been used might influence the privacy-related decision as well. For future studies, it is necessary to consider and investigate if the users have specific attitudes and privacy-related behavior preferences regarding the sensitivity of the collected data from the beginning or if it changes after a prolonged usage time. As Zimmer et al. (2020) point out, after initially changing privacy settings, users usually do not revisit them. In that case, features such as the deletion of collected data or other privacy settings that were added with a system update might remain unknown to the users.

Furthermore, Gouveia et al. (2015) revealed that their participants were using an activity tracking application only for a short period of time. Even if their study focused on the use of provided tracking information, their overall results could indicate that the users of activity tracking technologies are not actively engaging in the usage of the application over a longer period of time. This could also impact the interest to explore the privacy-related settings in more detail as compared to technology or SNSs, which the user becomes more familiar with over time.

The option of deactivating an account is beneficial, too, as it should also lead to the deletion of data at some point (depending on the company's terms and conditions). This means that from the perspective of taking care of one's data and, hence, sustainable information behavior, the most 'careless' action is either no action or just deleting the app from the phone. In contrast, the most responsible one is to deactivate the account or request the deletion of the data. It is interesting to note that 63% of the users from Germany would delete the application, and 55% would deactivate their account. However, the participants could choose several answers, meaning that those who would deactivate the account could also choose to delete the application. The gap between users from the USA, for those who would deactivate their account (66%) and those who would only or additionally delete the application (43%), is bigger than for users from Germany.

Finally, one should consider that the answers by current users might be influenced by the survey (increased awareness about data privacy issues and possibilities to take care of one's data) and leads to choosing answers indicating a more responsible behavior. Still, based on the outcomes, the US participants seem to behave in a more sustainable way in terms of data privacy at this point. Also, the chi-square test showed that the differences for data deletion and account deactivation were not significant within this sample.

9.4.2 Users' information-seeking behavior regarding company's data policies (RQ2)

This study's results regarding the users' interest in the company's data policies confirm the findings by Pingo and Narayan (2018). According to our results, 31% of 121 participants from Germany and 28% of 68 participants from the USA read the data privacy policies. A similar result is given for reading the terms and conditions. Out of 121 participants from Germany, 22% did read the terms, and so did 31% of 68 USA participants. Interestingly, in this sample, more participants from the USA (38% of 68 participants) researched the company's reputation for handling consumer data on the Internet. This activity is less preferred by the investigated German participants (22% of 121). There were no additional insights into the reasons. Still, it can be assumed that they are similar to the ones mentioned in the literature (e.g., information overload and no sphere of influence) (Pingo & Narayan, 2018). Again, the US participants seem to behave in a more sustainable manner. When looking at previous research in the context of culture and data privacy, Miltgen and Peyrat-Guillard (2014) found significant differences between northern and southern European countries in the perception of importance of responsibility (as opposed to trust) as well as between southern and eastern countries regarding the perception of information disclosure being a "choice" or being "forced". Even if these differences concerned other geographic areas, culture could also be an influential factor in the case of users from Germany and the USA.

As our results for RQ3 revealed, the participants of our study have privacy-related concerns. According to Dinev and Hart (2006), privacy concerns are defined as the threat that users' information is revealed without authorization. Could these concerns be mitigated if users actually read the privacy policies? Does the mistrust toward companies include questioning the validity of these policies? Here, the privacy paradox appears to encompass not only using the technology despite the (assumed) risks and threats but also information avoidance (not reading the policies) and post-usage data management (handling data after hypothetical discontinuance, see RQ1b). The fact that less than half of the participants did not read the information provided by the companies confirms the results by Vitak et al. (2018). Finally, Fietkiewicz and Ilhan (2020b) revealed that most of their survey participants did not believe that the GDPR will change the data privacy environment in the EU for the better. This could indicate that the trust in legal frameworks and policies, in general, is low, which could lead to decreased motivation to inform oneself about the data policies and the terms and conditions. In future research, factors like trust in the companies or in the legislation and their influence on information management and seeking behavior should be investigated.

9.4.3 Data Privacy Concerns Regarding Fitness Tracking Applications (RQ3)

This study builds on previous research by Lidynia et al. (2019) and expands its scope by including users from the USA. Similarly to Lidynia et al. (2019), who surveyed 38 users of fitness tracking applications and 16 users of fitness tracking wearables from Germany, our results show that users from Germany and the USA both have data privacy-related concerns. Regarding nearly all concerns, except for the one that the collected data is too sensitive, the medians of the agreement are quite similar. However, the distributions of agreements with several concerns differed significantly between participants from Germany and the USA. Generally, participants from the USA tend to be a little bit more concerned. Especially regarding such aspects as health insurances will access my data and use it against me, app companies will misuse my data and that I have no control over what will happen to my data. This could be due to less strict data privacy regulations in the USA. It would be interesting to compare the view on privacy-related aspects of non-users of this technology. According to Schomakers et al. (2019), the adoption of activity tracking technologies also depends on privacy concerns. Concerns such as data sensitivity and trust in data protection were identified as barriers to use activity trackers (Schomakers et al., 2019).

Finally, there was a difference in the agreement with the statement health insurances will access my data and use it against me, with which the US participants agreed more (when considering the distribution of the answers, not the median). This statement consists of two parts, namely the potential access to the data by health insurance companies and, additionally, their malicious exploitation of the data. It is hard to say whether the participants agree or disagree only with one part of the statement or not. At least German users benefit from health insurers' bonus programs (Henkel et al., 2018) and sometimes even pay less for the insurance as long as they maintain a fit lifestyle. Given the reputation of the health care system in the

USA, it is not surprising that the US participants were rather a little but more suspicious or worried about health insurers getting access to their fitness tracking data.

Where do these privacy concerns come from? Are they justified? It is necessary to investigate possible factors leading to perceived risks and privacy concerns. For example, news about data misuse by companies, e.g., the case of Strava or the Cambridge Analytica scandal in the USA, might influence US-American users' trust and concerns. Indeed, previous investigations showed that US-American users of SNSs have more privacy-related concerns (Wang et al., 2011), which also seems to be true for activity tracking technologies.

Even though users are worried about potential risks, it is impossible to avoid all the possible threats. When they are willing to use activity and fitness tracking technologies to their fullest extent, they have no other choice than to run the risks. The participants' comments and previous research indicate that several parties must be involved to improve this situation. Therefore, we suggest three essential steps. Firstly, the state (government, legislature, judicature) must create an adequate (international) legal framework and execute it. Here, one of the biggest challenges is the transatlantic data transfer and the inadequate agreements between the USA and the EU. Secondly, given that companies comply with legal norms and develop applications with high data privacy standards (including privacy by default and privacy by design), they need to win users' trust that this is actually true. Still, given the several data breach scandals (e.g., MyFitnessPal or Strava), it seems that at least in terms of data security, there is room for improvement on the companies' end. Furthermore, companies need to provide short, user-friendly, and readable data privacy information and features. Both the companies and the legislation seem to lack trust from the consumers (which might negatively influence the users' information management behavior). Thirdly, and finally, the users have to develop sustainable information management behavior.

9.5 Conclusion and Limitations

Previous studies on activity and fitness tracking and data privacy mainly focused on technological aspects. Regarding culture-dependent differences, most of the previous studies focused on SNSs, and there is only scarce scientific evidence within the activity tracking technology domain. This study broadened the existing research by focusing on activity tracking and fitness tracking application users' awareness, information management behavior, and concerns related to data privacy from Germany and the USA.

Many of the participants were not aware that they could request the deletion of the collected data. What should be kept in mind is the response bias. It is questionable whether users were inclined to give the more favorable (but not necessarily correct) answer to the question Did you know that you can request the deletion of all data that was collected? Often survey participants tend to choose an answer that is socially more desirable. However, over half of the current users would potentially deactivate the account upon opting-out. The results indicate relatively low interest in taking care of one's data, which might either be explained by indifference, lack of knowledge, or only lack of trust that the data will be deleted. To better understand the reasons, it is necessary to conduct more studies, preferably in-depth interviews with former and current users of fitness tracking technologies. Here, the trust in the companies and generally trust in the legislative regulations (e.g., GDPR) might influence the behavior and decision to be more responsible with data that has already been collected. During those in-depth interviews, participants could show their privacy settings and explain why they changed or did not change them. It would help to better understand the users' decisions and to find the reasons behind their behavior, which could involve simple disinterest or mistrust in companies and legal enforcement.

Moreover, it remains open whether the surveyed data privacy concerns are only transferable to wearable technology or to the view on privacy in other areas of everyday life in general. Further studies are needed to better determine users' opinions on data privacy and their trust. More trust can lead to feeling more secure with personal information being shared with the device and application. Therefore, it is advisable to integrate overall privacy-related questions regarding digitalization in general (not specifically related to activity tracking technologies) in future studies.

As already indicated in similar research, most users do not read the data privacy policies, terms, and conditions. It could be explained by information overload and lack of choice (one needs to accept the terms to use the application) or lack of trust in these policies' validity or effectivity. For more concrete reasons, a follow-up study is necessary. Such a study could focus, for example, on the question of whether the users are actually concerned when accepting the terms and conditions or privacy policies and if they think twice before accepting them.

Regarding data privacy concerns, users are aware of the potential risks. To mitigate these risks, the involvement of several parties is necessary, i.e., the government, the companies, and the users, who need to develop certain information behavior to handle and share their data more considerably and in a sustainable way. All in all, the results indicated a not very durable information behavior of both user groups—German and US-American. Still, whether due to less beneficial and effective legislation or other reasons that could be investigated in the future, the participants from the USA appear to have a more conscious attitude toward data privacy. Data privacy and protection in all areas of our everyday life, and the health and fitness area, in particular, should not be neglected. User-centered research studies showed that companies must focus on improving the security of consumer data to avoid misuse and unauthorized access and possibly increase the trust of the consumers.

Further, terms and conditions, as well as data protection and privacy policy statements, need to be consumer-friendly (i.e., informative, short, easy to read). Users need to be informed about their data, for example, if other parties have access to it or where it is being stored. Apart from the companies' sphere of influence, the users themselves need to become more information literate to manage their data adequately (e.g., after stopping to use an application), to be more critical and aware, but not necessarily afraid of using the technology. Being critical and aware of the faith of personal data as well as about the information management behavior might be affected by the legal infrastructure within a country and the respective cultural influences.

Previous investigations already thematized the privacy paradox in detail (e.g., Pentina et al., 2016). Even though users of many new technologies have privacy concerns, they still adopt and use them. Pentina et al. (2016, p. 417) described this behavior as follows: "risk perception does not have a strong enough influence on actual risk-avoiding behavior." Our results confirm this statement, as we saw that the users of activity tracking technologies have several privacy concerns but continue to use the wearables and mobile applications. Interestingly, their information management, as well as seeking behavior, were also not sufficient (or rather contradictory when considering their concerns). Less than half of the participants did not inform themselves or read the information offered by companies. In the future, it is not only important to investigate if the information provided by companies needs to be restructured and shortened (made easier and more convenient to read), but also to investigate if users know what the information actually means and what happens with their data. As Pingo and Narayan (2018) already mentioned in their study, offering privacy protection is only one side of the coin. On the other side, people need to be (or become) privacy literate in order to understand the meaning of the provided information and to be able to act accordingly.

Finally, our results indicate that the self-responsibility of the users should be investigated in the future from other perspectives that might have a significant impact. Despite the cultural background, the age of the users might influence their behavior. Miltgen and Peyrat-Guillard (2014) detected cultural and generational influences on privacy concerns in Europe. Apparently, younger users have a more positive attitude toward data management. They feel more responsible and "are more confident in their ability to prevent possible data misuse" (Miltgen & Peyrat-Guillard, 2014, p. 2). It is crucial to focus not only on generation-dependent differences but to take a deeper look into why these differences arise. One possible reason could be the level of information (privacy) literacy.

As for the limitations of this study, online surveys always bear a lot of challenges. One of them is the non-response bias, meaning that users who did not respond to our questionnaire might demonstrate different features and behaviors from those who responded. Furthermore, the aspect of "origin" or "culture" becomes more complex due to globalization—many Germans might live and work in the USA for several years and vice versa. The cultural diversity in more cosmopolitan regions makes a strict distinction between "German" and "US-American" users challenging. The participants of the survey were only asked about the country of their origin. Finally, the sample acquired from the online survey is not representative of the population of activity tracking technology users from Germany and the USA. The results and the conclusions drawn are primarily valid for our sample and only give indications that could relate to the general population of activity tracking users, which should be investigated in more detail. Further, the samples from the two investigated regions were not equally distributed as the sample includes 121 participants from Germany and 68 participants from the USA.

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10 Discussion and Conclusion

This thesis investigated the research domain of activity tracking technologies from an information science perspective. This leads to holistic and thorough insights while focusing on two of the core characteristics of information science - information and information behavior. Currently, there are barely investigations from an information science perspective. In the last few years researchers started to address this research gap (see for example Feng & Agosto, 2017, 2019a, 2019b; Hirvonen, Pyky, Korpelainen, & Huotari, 2015; McKinney, Cox, & Sbaffi, 2019; Pingo & Narayan, 2019; Shin, Cheon, & Jarrahi, 2015; Shin et al., 2019) within this domain. Activity tracking technologies opens up a diverse research field where different disciplines encounter and investigate different aspects, starting from accuracy, medical trials, interventions, acceptance, engagement, to information behavior (Shin et al., 2019). Overall, for a holistic perspective from the information science domain this thesis shed light on the self-quantified information behavior, motivations to join fitness and health-related communities within Facebook, and privacy-related concerns. The first RQ emphasizes users' self-quantification information behavior.

Part 1: Self-Quantified Information Behavior
RQ1: To what extent do the ATTs enable effective self-quantification behavior from an information science perspective?

This thesis started with an investigation of users in Germany and the USA regarding the perceived service quality acceptance of ATT and their attitude towards sharing collected data with health insurance funds (Chapter 2). In this investigation, participants are the main actor, and ATTs are characterized as a facilitator. The investigation presented in Chapter 2 provided empirical insights from an information science perspective as there were barely any investigations on this topic. Answering the question to what extent ATTs are useful in a first step, the ISE model was applied to understand users' satisfaction towards self-quantification by using ATTs.

Further, this study raises awareness regarding the question - who is and should be responsible for supporting users reaching a healthier life by using the self-tracked data? Within Library Science, everything regarding Information Behavior is often linked to the responsibilities of libraries. Should the health insurance companies be the responsible entity to support users? Interestingly, even though there were some slight differences, participants from the USA and Germany mainly agreed that they would share their data with health insurance companies to receive financial support for lowering health insurance contributions. Sharing data with other entities enables insights into one's sphere of privacy. Regarding the fact that already some universities in the USA involve ATTs (University Oral Roberts, 2016), should the responsibility for developing and supporting skills by shifted to educators? This is a difficult task in many ways - as they are sharing personal information within an environment where they are permanently getting assessed by their performance.

Participants within this investigation perceived the service quality as sufficient. For example, they agreed that those ATTs support self-quantification of the behavior and that ATTs enable improvement of the fitness level as well as of the health status. Therefore, information offered by ATTs support users towards a healthier lifestyle. As participants also mainly agreed that the ATTs are fun and impact their behavior (e.g., feeling better, taking stairs instead of the elevator) those technologies can be integrated into everyday life and interventions as a first step towards a healthier lifestyle.

The investigation of the HCI shaped through information within this thesis enabled to gain insights into how people feel and behave. Interestingly Chapter 2 also showed that gamification elements (e.g., badges, rankings) improve physical activity behavior and thereby support the self-quantification behavior. Those gamification elements have the potential to acknowledge users' physical activity.

While the use of ATTs enables real-time observing and gaining awareness about oneself, to what extent can the concept of information literacy enable a thorough insight towards users' use of those wearable? Are users able to recognize needs that can transform in information needs? Chapter 4 underlines to what extent users estimate and use self-quantifying activity and health-related information. Thereby, Chapter 4 concentrated on the information need and divided the information provided by ATTs into three levels regarding their richness. Most of the participants already knew the heart rate zones and sleep stage characteristics explanations and perceived them as understandable and useful. Interestingly, investigating the information behavior underlines that those explanations offer the potential to learn new things. Therefore, users are not only gaining awareness and can self-quantify their behavior they are also gaining new knowledge. The investigation stresses that also the information itself is important. They agreed that the explanations were not overloaded and are easy to understand regarding the difficulty of sentences and words (see for example, *"Cardio (70-84% max heart rate) is the medium to high intensity exercise zone. In this zone, you are pushing yourself but not straining. For most people, this is the exercise zone to target"*). Overall, Chapter 3 confirmed that self-quantification benefits through the information content and its readability (e.g., interesting, not too long and easy to understand).

Most participants agreed that they have an information need. Chapter 2 confirmed that ATT are useful devices to counteract those knowledge gaps. Through self-quantification, users improve physical activity behavior, recognize salience/differences, and assess their behavior. Summarized, ATTs are indicated as a useful starting point. Chapter 3 also focused on different information types. The insights revealed that they do not use different information types provided by ATTs equally. Even if aggregated data provides more richness, raw data is more preferred.

One central insight of this investigation is that it is crucial to differentiate between reflecting and adapting a behavior primarily based on the explanations provided by ATTs. Adapting requires much more action than reflecting on a behavior. Adaption requires connecting the gained knowledge with previous knowledge.

Apart from understanding how information is used, learning is an activity that is also of enormous interest in information science. The progress and duration of learning is nothing predictable; instead, it requires adopting a behavior until it is a habit. Chapter 5 offered theoretical insights to what extent different gamification elements within activity tracking technologies could help to learn to be physically more active.

Within Chapter 5 different theories were used to better understand gamification elements' potential to motivate users to learn to be physically more active. Interestingly, Chapter 2 already showed that gamification influences the perceived usefulness (improving health and fitness) and impacts the behavior (e.g., taking more often the stairs).
Information Science can offer valuable information, especially by looking into textual feedback on how to conceptualize gamification elements such as documentary features and progress bars. Further, the thesis offered first hints that it is useful to think about gamification elements that aimed to educate users and disseminate valuable information. Together, companies, users, and information professionals can counteract amotivation (lack of motivation) and support users to start and continue to self-quantify their behavior and to improve physical activity. Chapter 5 underlines that it is challenging to generalize those gamification elements as users are differently motivated and might also have different goal-settings. Further, gamification is not the key to success. It is a tool that needs to be elaborated, especially concentrating on the information content. Gamification indeed can support users to be physically more active and to continue self-quantified behaviors. The effectiveness and long-term impact are questionable, especially since goals are changing, and individuals' motivational reasons and goal-orientation differ.
Further, this thesis revealed that the responsibility to successfully self-quantify and improve physical activity behavior is not solely the user's responsibility. Even though a user might not understand the information, it can be the information itself and its stiffness and superficiality or complexity and, more importantly, how the information is constructed and integrated. Aspects such as perceived impact on the behavior and usefulness of those information systems enable a positive self-quantification behavior towards reaching a goal or feeling well.

Self-quantification through ATTs already supports users trying to be physically more active. As the concept of information behavior in this thesis is broadly defined (Zimmer, Scheibe, & Stock, 2018) information science needs to critically reflect why there exist many health and fitness-related groups, especially if those ATTs have the potential to support users to self-quantify their behavior. Further, from an information science perspective, it is crucial to understand if users have an information need and seek information that ATTs could not provide. The next section will conclude the main insights and implications referring to Chapters 5 and 6.

Part 2: Information Behavior within Health and Fitness-Related Facebook Groups
RQ2: Which gratifications and other motivational sources lead ATTs users to join health and fitness-related Facebook groups and to what extent do users' characteristics influence information behavior?

Health and fitness-related Facebook groups, primarily focusing on ATTs, are barely investigated, and it is less known why users of ATTs join those groups. However, HCI investigations already showed that the health-related Facebook groups (e.g., vaccine and other mental-related groups) enable the users to receive emotional support and obtain information. Diverse interests (e.g., political, housekeeping (e.g., cooking), health, and fitness) are shared by users of the same interest topic-related Facebook groups. Investigating the information behavior of users within those groups, applying U&GT enables us to understand if they are seeking and receiving information and if there are other reasons why they joined those groups. Indeed, social media, especially SNSs, such as Facebook, are surrounding our everyday life. To what extent are those groups supportive? The insights by Chapter 5 and 6 stress that users indeed have an information need that explains why they are joining those health and fitness-related Facebook groups and that these groups are sufficient regarding offering the needed information. This could lead to the assumption that the ATTs do not offer the needed information or at least are not offering all the answers users desire. Nevertheless, even if this is the case, users would not stop to use ATTs if they would resign from those health- and fitness-related Facebook groups. The investigation assigned to Chapters 5 and 6 underlines that self-quantification does not only refer to using the ATTs, as the investigations showed even if users disagree that they joined to share their achievements badges, but those groups also enable to share that information with other users. Therefore, self-quantified activities have the potential to affect the digital social environment. Further, users enable other users to partake in those activities as sharing the own self-quantified data include health metrics such as steps, heart rate, distance, GPS tracked running routes and much more. The presented investigation also indicates that self-quantification behaviors and questions that arise are information needs that are shared with other users of self-tracking activities. Those health and-fitness related Facebook groups build a community around specific health related topics to share common goals and motivations. One posting (see Chapter 5) is one example for content that is shared within those groups. The users created a post that includes the own experience and information about sleep tracking. The user wanted to know how the sleep tracking looks like to compare the own behavior and the accuracy of the ATT. Therefore, the need to seek information is more about sharing an experience or getting to know other users' experiences instead of getting to know if something is right or wrong. For more evidence, future research needs to concentrate on the content itself. Still, first insights assume that self-quantification requires sharing and comparing experiences and similar situations with other self-tracking users. Even though users agreed that the health and fitness-related groups enabled users to obtain information, the quality of that information is still questionable. This insight requires a profound characterization of different kinds of information (knowledge-based, experience, assumptions) to understand better the sought and obtained information content within those groups. Regarding information behavior, this insight crystallized a further fundamental characteristic of SNSs - the vitality and community structure. There is space for discussion, differences of opinion and critical debates while google mainly offered a few hits with the direct answer or further sources. Therefore, the need to seek information within those Facebook groups already suggests that it does not need to be a fact-related question but rather an experience-based one. Another advantage of these groups is the possibility of asking queries or asking twice if something was not understandable. The question-answer environment is dynamic. Further studies are needed in the future, as the need to receive information does not necessarily indicate that users also actively ask something. Instead, answers they are seeking could already be posted or offered within the groups. Chapter 5 revealed that information was the most substantial sought gratification, while self-presenting was the less preferred one. Through self-quantified tools such as ATTs, users have the possibility to share their tracked information about themselves, such as how many steps they achieved or which running route they run. While the U&GT offered a thorough understanding of why users decided to join those groups, the SDT offered insights which motivational reasons underlie. Combining those two approaches does not only reveal why users are mostly joining those groups. They enjoy those communities, but in the case where they seek self-realization, it is associated with the Facebook groups' values and aims. This indicates that self-quantified behavior can be supported through those communities if one needs endorsement and a safe place to share achievements. Interestingly, if users are seeking information, they were generally intrinsically motivated. Chapters 5 and 6 outlined the strengths of U&GT and SDT. It enables a manifold insight into how motivational sources and the need to seek gratifications can correlate with each other. Further, as Chapter 5 offered insights, even if users agreed that they joined those groups because they sought information, they would not stop using their ATTs if they leave those groups. Therefore, it is evident that users can also have questions that do not primarily affect the self-quantification activity itself regarding continuing to use those ATTs.

Chapter 6 investigated if there are gender- and generation determined-differences regarding the motivation to join those groups and sought and obtained gratifications. There were no gender-determined differences and only slight differences regarding generations. This revealed that users' needs in this sample, regardless of gender, are similar. However, there are existing generation-determined differences regarding the sought gratification information. Even if all four generations Silver Surfers (born before 1959, hence at least 60 years old), Gen X (or Digital Immigrants, born between 1960 and 1979, hence 40-59 years old), Gen Y (also Digital Natives or Millennials, born between 1980 and 1995; between 24 and 39 years old), and finally, Gen Z (born after 1996, hence, up to 23 years old) mainly agree that they seek information, Silver Surfers seem to agree a little more. Studies already confirmed that particularly the elderly population is joining Facebook. Those communities could support the elderly by offering information and enabling support to be physically active through encouraging and starting challenges.

As those insights already show, self-quantification behavior affects many areas where information is shared and collected. Even though within SNSs, achievements that are shared or running routes are disclosing personal information. Measured and offered information provided by wearables are deposited within digital clouds. As some of these data pieces might be perceived sensitive, the last part of this thesis thematized users' privacy-related behavior and concerns regarding ATTs.

Part 3: Self-Quantified Privacy-Related Behavior and Concerns
RQ3a: What are the privacy concerns regarding ATTs?
RQ3b: What is the privacy information behavior of ATTs users?

Interestingly, the investigations (Chapter 7 and 8) revealed privacy-related concerns between different kinds of users. Indeed, those concerns could be caused by institutions (top-down approaches) and overall data breaches and lack of trust in companies. These chapters only investigated to what extent users have privacy and security concerns but not why. As more user-centered investigations are needed within the data privacy environment regarding ATTs, these chapters work towards shrinking the gap.

It is crucial to understand how the top-down legislation by federal institutions is perceived in the first step. If there is already skepticism, this could influence the overall attitude towards the protection of own data. Chapter 6 showed that nearly all participants are aware about GDPR (top-down legislation), but users are critically assessing the effectiveness of GDPR. Interestingly, there were slight differences regarding the fact that users who believe in the effectiveness of GDPR neither agree nor disagree regarding the statement if they feel safe about their privacy data regarding GDPR, while those who do not believe in the effectiveness disagree.

Users, former users, and non-users perceived data pieces as GPS, contact/friends as highly sensitive, whereas data pieces such as step count and burned calories were not perceived as sensitive. Furthermore, Chapter 8 underlines that one kind of user group have perceived all data pieces as sensitive except for the data piece gender. In contrast, another user group estimated nearly all data pieces except for GPS, Contact friends, and emails as rather not sensitive and only real name, birthday, interest groups, menstrual cycle as neutral. All three user groups perceived contact and friends, email and GPS as sensitive.

Overall, Chapter 9 confirmed that there were primary privacy-related concerns regarding ATTs users and also some significant differences. Users of Germany and the USA users mainly agreed to have privacy-related concerns. Those concerns are being afraid of having no control over what will happen with their data or, for example, it will be possible to create detailed profiles based on the collected data. German users tend to be less afraid that health insurance companies could use their data than users from the USA, even if the median value equals 4 ('Agree'). One reason for this could be the different health insurance systems within Germany and the USA. Those results confirmed the privacy calculus phenomenon as those users are active and are using their wearable while having privacy-related and security-related concerns. Further, especially with having the privacy-related information management behavior in mind and to what extent users take responsibility of their data, Chapter 9 offers interesting insights. As Chapter 6 confirmed, users do not seem to be convinced about GDPR effectiveness. This could also influence the behavior regarding how to manage data in case if one is stopping to use those ATTs. Not even half of the German participants would request the deletion of data in such a scenario. They would delete the application and deactivate their account instead.

Interestingly at least half of the participants of the USA would request the deletion of data. Even if those options are available, such as a request to delete the collected data, users need to be aware of these options. No more than half of the German participants and less than half of the USA participants did know that this option exists. This indicates that users are not engaging with privacy-related settings. While users would actively decide after hypothetically stopping to use the application, users' information-seeking behavior is critical. About 52% of the German users did not inform themselves about data privacy. Less than half of the participants read the privacy policy, terms, and conditions or searched for further information within the internet. However, users in the USA seem to be more open to privacy-related information, which could be reasoned by different legislation.

Conclusion and Implications

This thesis opens a new research realm for the information science discipline. With its concepts it enabled to gain an holistic overview about users' health information behavior regarding ATTs and shed light on different aspects. The concept of information behavior enabled to counteract the gap of data-centric research and therefore, to provide useful insights to understand the Human-Information Interaction (HII) (Shin et al., 2019).

With this step, highlighting a new research field within information science, the thesis encourages information practitioners and researchers to continue investigating ATT from an information science perspective while applying their concepts and methodologies. As long as we are surrounded by manifold information, anytime and anywhere, skills to be able to deal with varying information, to use those information adequately, and to make-decision will continue to face the 21st century's society and the research realm.

Even though this phenomenon is fascinating, this thesis revealed several challenges that need to be addressed in future studies. Today's society is challenged by the boon and bane of empowerment to consume and produce information in a commendable and critical way. Indeed, self-tracking characterizes an autonomous person who is empowered to take action and make own decisions. But this does not mean that the understanding of those self-tracked data depends solely on the users. As a society and as information professionals our insights can contribute in two main ways following the first part of this thesis:

- (1) We need to support the development of those technologies (e.g., regarding gamification elements and the information content itself) to support users perceived usefulness.
- (2) As there are already many information literacy instructions at university and library levels, we need health information literacy, data literacy workshops regarding the self-quantification of health and fitness-related information. This should not be the sole responsibility of users. At least as information professionals, we need to support users to develop skills to seek further information, be able to adapt that information, and overall to question that information critically. Indeed, it would be too much to ask for medical expertise, but information professionals have the expertise to seek and use information adequately and to forward those skills.

Further, the second part of this thesis highlights the impact of U&GT and SDT regarding health- and fitness related Facebook groups and why users of ATTs are joining them. In fact, those groups offer opportunities for information science researchers to better understand the different sources within the digital environment. Apart from evident-based knowledge (books, scientific literature, news) those information and experiences within the SNSs are lacking the check of quality. Those online communities are a protected space without being judged by institutions, such as doctors, for example. But the challenge arises as those experiences and advice are generally not proved. Therefore, users need to critically reflect on shared information if they look for adequate information instead of estimation and experiences. Those two chapters offered the following implications:

- (3) Within the context of self-quantified behavior, there are manifold groups within Facebook that enable disseminating information and consuming information and sharing experiences and motivating each other regarding the groups' description. To better understand those information sources' needs (here Facebook groups), especially for sharing experiences and receiving subjective estimations, it is inevitable to investigate the information content. As users were mainly intrinsically motivated and sought information, the behavior and needs of different gender and generations could reveal differences regarding the differentiation of seeking various information content. Such a subdivision in different types of information might show gender-determined differences.

- (4) There were barely generation-determined differences regarding seeking information. Especially as older people seem to join Facebook, more and more future studies need to focus on this target group. Regarding the self-quantified behavior, those groups, mainly where mobility and social environment could be restricted, could enhance the self-quantifying activities in many ways.

Apart from the information behavior regarding seeking information, using information, and sharing information, data privacy-related information behavior is crucial to offer a holistic view of ATTs from an information science perspective. Based on the chapters' insights, this thesis reveals several crucial implications to support users and create at least, from a user-centered view, sustainable and reasonable privacy-related information behavior. Information Behavior is affected by the omnipresence of digitization. The new ways of how data is collected and stored raise critical questions such as to what extent those data are vulnerable and to what extent users could protect their data. Therefore, the following two implications are crucial to achieve supporting users to create awareness and a sustainable privacy-related behavior:

- (5) Users need to take action in the future. At least information professionals need to raise awareness to what extent they can control their data and find information about it. As described in Chapter 9, "the most 'careless' action is either no action or just deleting the app from the phone." Even if most data-privacy regulations are top-down processed, users still can protect their data to some extent. Indeed, this requires engagement with privacy-related information and the meaning of the information provided within data privacy policies or terms and conditions.

- (6) According to the concept of IB, reasons why users are not reading data privacy policies, apart from lack of motivation, could be information overload. Information overload leads to information avoidance. Further, apart from information overload, it is also the language that is used within privacy and policy terms. Further studies need to investigate to what extent the sentences and terms are difficult to understand.

Overall the results of all chapters, according to the conceptual triad by (Shin et al., 2019), stress the importance of information science and its valuable insights. The results of the chapters mainly provide two valuable insight: First, the information science domain discovered a new research area and offered valuable insights towards the self-quantified behavior from different approaches. Second, developers and users can benefit from the insights since the user-centered studies were aimed at raising awareness and supporting users in their self-tracking behavior.

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Author Contributions

The publication used for this thesis have been slightly altered. This includes correction of grammatical errors or typing mistakes, formatting, design of the figures and tables (to ensure consistency), correction and unifying references.

Chapter 2:

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Conceptualization, methodology, investigation, data curation, manuscript preparation (2.2., 2.3, 2.4, 2.5), review and editing, visualization

Chapter 3:

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Chapter 4:

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Conceptualization, investigation, data curation, manuscript preparation (parts 4.1, 4.2, 4.21., 4.2.2, 4.3, 4.4., 4.5), visualization, final editing

Chapter 5:

Ilhan, A. (2018). Motivations to join fitness communities on Facebook: Which gratifications are sought and obtained? In G. Meiselwitz (Ed.), *Social Computing and Social Media. Technologies and Analytics, (Lecture Notes in Computer Science book series* (Vol. 10914, pp. 50–67). Springer. doi: https://doi.org/10.1007/978-3-319-91485-5_4

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Chapter 6:

Ilhan, A. (2020). Users of Fitbit Facebook groups: a gender- and generation-determined investigation of their motivation and need. In G. Meiselwitz (Ed.), *Social Computing and Social Media. Design, Ethics, User Behavior, and Social Network Analysis. HCII 2020, (Lecture Notes in Computer Science* (Vol. 12193, pp. 513–533). Springer. doi: https://doi.org/10.1007/978-3-030-49570-1_36

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Chapter 7:

Fietkiewicz, K. J., & Ilhan, A. (2020). How do users of activity tracking technologies perceive the data privacy environment in the EU? *iConference 2020 Poster Proceedings*.

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Manuscript preparation, review and editing, visualization

Chapter 8:

Fietkiewicz, K. J., & Ilhan, A. (2020). Fitness tracking technologies: data privacy doesn't matter? The (un)concerns of users, former users and non-users. In *Proceedings of the 53rd Hawaii International Conference on System Sciences, January 7-10, 2020, Grand Wailea, Maui* (pp. 3439-3448). ScholarSpace.

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Conceptualization (partially), empirical investigation, manuscript preparation (Introduction, Methods)

Chapter 9:

Ilhan, A., & Fietkiewicz, K. J. (2020). Data privacy-related behavior and concerns of activity tracking technology users from Germany and the USA. *Aslib Journal of Information Management*. https://doi.org/10.1108/AJIM-03-2020-0067 (in press).

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