Digitalization of the Individual – An Empirical Investigation of the Self-Tracking Usage Behavior

Dissertation

zur Erlangung des Grades eines Doktors der Wirtschaftswissenschaft

der Rechts- und Wirtschaftswissenschaftlichen Fakultät

der Universität Bayreuth

Vorgelegt

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Tag der mündlichen Prüfung: 10. Oktober 2019

Stay hungry. Stay foolish.

Steve Jobs, 2005

I deeply want to thank my colleagues, friends and family for their great support within the development of this dissertation during the last five years. Without them this project would not have been possible. My special thanks go to my doctorate supervisor Nils Urbach for his continuous feedback and advise and to my co-authors Arne Buchwald, Albert Letner, Niclas Nüske, Timon Rückel and Jurij Pfeiffer for their enthusiasm and resilience during the development of our research papers. Lastly, I also want to thank my wife Melanie for her great support and patience through all ups and downs that came along.

Abstract

Digitalization is not only impacting businesses and business models but also society and ultimately each individual. In this context, the individual is affected in all areas of life – being it in the role as member of society, employee or private person. Regarding the private person, the impact of digitalization includes the trend to use wearable self-tracking devices such as smartwatches or fitness wristbands. Such devices enable continuous measurement and analysis of bodily functions, thus increasing the users' convenience and self-determination regarding maintaining and promoting well-being, fitness and health. Based on this trend, an entire ecosystem evolved consisting of manufacturers and digital as well as traditionally "offline" service providers, such as physicians and health insurance companies, providing customers with tailored goods and services around self-tracking.

In contrast, from a scientific perspective, little research addressing this development has been conducted so far, although it is crucial for manufacturers and service providers to know how their customers use their devices and services. Therefore, this dissertation aims to contribute to the understanding of usage behavior for wearable self-tracking devices.

To do so, four research essays have been written to analyze different facets of usage behavior. Essay 1 and 2 focus on the acceptance respectively post-acceptance phase of wearable self-tracking devices, introducing determinants that foster initial acceptance and continuance intention as well as discontinuance intention. Essay 3, by contrast, sets focus on the privacy attitude of wearable self-tracking users by showing how perceived privacy risks and perceived benefits influence the willingness to disclose personal self-tracking data to health insurance companies or family physicians. Finally, Essay 4 focuses on the users' fundamental motivations to engage in the practice of self-tracking. Therefore, the interplay of motivations, usage and motivation fulfillment as well as the impact of the utilization of gamification elements is presented.

The research results not only give practical guidance for manufacturers and service providers of wearable self-tracking devices but also advance theoretical knowledge on usage behavior in the context of personal self-tracking.

TABLE OF CONTENTS

Introduction to „Digitalization of the Individual – An Empirical Investigation of the Self-Tracking Usage Behavior”

Abstract

In this introduction to my dissertation I present a comprehensive overview of the self-tracking phenomenon and resulting usage behavior. Therefore, I first outline the impact of digitalization on the individual before I explain the internet of things as underlying technology for and the characteristics of wearable self-tracking devices. In the following, I describe the motivations and derived research questions which have been elaborated within four different research essays, followed by the introduction of the research structure and design. Afterwards, key results and implications of each essay for theory and practice are presented. The introduction closes with an overview of the limitations of the dissertation and an outlook on upcoming developments in the domain of self-tracking.

Keywords: Digitalization, Self-Tracking, Wearable Devices, Digitalization of the Individual

Table of contents - Introduction

1. Introduction

With the ongoing evolution of existing technologies such as the Internet and mobile devices as well as disruptive innovations such as cloud computing, Internet of Things, artificial intelligence and Blockchain to just name a few, in 2019, digitalization still is a dominant topic in business, society and for private persons. Traditional businesses are forced to adapt their business models to changing customer demands and competing new digital services in order to preserve their market position. In addition, technological innovations at the shop floor and the supply chain as well as employee demands for modern forms of working lead to an adjustment of business processes and organization (Urbach and Ahlemann 2019). In society, digitalization creates new forms of social, political, and cultural participation and exchange. The constant and rapid availability of information allows societies to be closer to worldwide socio-cultural topics and to participate actively. However, this opportunity comes along with both chances and risks. While it can facilitate participation (for example the EU conducted an open survey among EU citizens concerning the time change (Prange 2018)) and organization of protest, the open and unverified distribution of information is cause for the current discussion about electoral manipulation and “fake news” (Allcott and Gentzkow 2017).

At the level of the individual, digitalization brings changes with regard to various roles (Vodanovich et al. 2010). For the individual in the role as member of society digitalization opens more ways for participation in socio-cultural processes (Entman and Usher 2018; Estellés-Arolas and González-Ladrón-de-Guevara 2012; Ovadia 2014) For the role as employee digitalization brings more flexibility for the organization of work (Messenger and Gschwind 2016; Sutherland and Jarrahi 2017; Weiß and Leimeister 2012) and for the role as private person more convenience and self-determination in communication, entertainment, learning, mobility, living as well as well-being and health (Bugeja et al. 2016; Higgins 2016; Kizilcec et al. 2017; Ling and Campbell 2017; Lupton 2014b; McDonald 2016; Remane et al. 2016).

In this regard, the trend to use wearable self-tracking devices for supporting well-being, fitness and health has emerged in recent years and is still growing (IDC 2018b). These personal consumer devices mostly come in form of wristbands or smartwatches (Mainelli 2018), are often worn all day long or event at night and allow their users to conveniently track various aspects related to bodily conditions. In addition, the gathered data can be interpreted, compared, discussed and ultimately used to initiate positive personal change and new habits without the need for external consultation (Kettunen et al. 2019a; Kettunen et al. 2019b; Lupton 2013, 2014b).

However, these positive changes and new habits are only possible if the following conditions align. At first, potential self-tracking device users must initially accept the technology, that means buying a device and starting the usage. Second, usage must be continued regularly and over a long period of time in order to facilitate the collection of enough data that allow to draw insightful patterns from it. Third, it is necessary that users are willing to disclose their personal data to certain service providers to enable benefits from data-driven services. Finally, it is also necessary that users are motivated and perceive their motivation as being fulfilled through the engagement in self-tracking.

To better understand these different conditions, previous research on the usage behavior of technology could be consulted. However, due to the highly personal and intense connection of wearable self-tracking devices with their users, their unique characteristics should be considered as a separate context compared to other consumer technologies. Hence, established research models that have been verified to describe technology usage behavior in other contexts might not be applicable for the specific self-tracking context. Also, new context specific constructs that have not been considered so far could be of importance.

Therefore, the overall goal of this dissertation is to empirically investigate the usage behavior for wearable self-tracking devices and thus to extend the theoretical knowledge of this new research context. In addition, from a practical perspective, guidance shall be provided to manufacturers and service providers how wearable self-tracking devices and services have to be designed in order to be able to ensure a positive user experience and perceived benefits. To achieve this goal, this dissertation follows a cumulative research approach. Four separate research essays analyze the topic from various angles and answer six different research questions concerning the acceptance and post-acceptance phase, data disclosure and privacy attitude of users and the role of motivations and gamification.

In addition, this introduction consolidates the four essays and provides a comprehensive view on the topic. To do so, in Section 2 of this introduction I explain the concepts and developments within the topics of Digitalization of the Individual, Internet of Things and Wearable Self-Tracking Devices which form the basic framework for this dissertation. Afterwards, I explain the motivations, derived research questions and conceptual development for the four essays in Section 3, followed by the introduction of the research structure and method as well a brief presentation of research results Section 4. Finally, the overall implications for theory and practice, limitations and an outlook are presented in Section 5.

2. Foundations

2.1. Digitalization of the Individual

When it comes to the term digital, two manifestations arise. At first, digitization is defined as "the process of changing from analog to digital form, also known as digital enablement" (Gartner 2019a), for example by changing from analog music formats (e.g. gramophone record) to digital formats (e.g. mp3). Based on digitization, the term digitalization is defined as "the use of digital technologies to change a business model and provide new revenue and value-producing opportunities" (Gartner 2019b). For example, the offering of movies and series as a digital streaming service over the internet (e.g. Netflix or Amazon Prime) emerged as a new business model in the industry and forced back traditional offline video stores. However, when broadening the view, the definition of digitalization is too narrowly considered. During the last ten to fifteen years new innovations and the evolution of existing technologies gave rise to changes not only on the business side but also in society and on the level of each individual.

Looking deeper, the individual is simultaneously affected by digitalization in their various roles – as employee, member of society and private person (Vodanovich et al. 2010). For the individual in their role as employee, digitalization enables new ways of working and changes the relationship to the employer. For example, the term consumerization describes the trend that new technological innovations (e.g. smartphones, social media), that originated in the consumer sector, increasingly infiltrate the corporate environment as employees demand these technologies as the standard to which they are used to in their private life (Weiß and Leimeister 2012). One step further, since modern information and communication technologies enable to communicate from worldwide locations at any time, traditional working patterns dissolve. The so called "anywhere office" becomes more and more popular. It allows to work increasingly from home and at points in time which fit best to the individual need to balance work and life (Messenger and Gschwind 2016). An even more disruptive working trend is proposed by the so called "digital nomads". These mostly young and well-educated digital experts work from abroad for various employers on a freelance basis, thus illustrating exactly the opposite of a traditional working pattern (Sutherland and Jarrahi 2017).

For the individual being a member of society, digitalization allows to participate more actively in socio-cultural processes. For example, with new media services, especially through the features of social media like facebook or twitter, more information is available in shorter time which allows not only to get a more sophisticated picture about a certain topic but also to actively take part in political, social and cultural debates (Entman and Usher 2018). Also, the worldwide availability of information can be used to take part in research, innovation and culture. For example, research platforms like researchgate or Academia foster the exchange on fundamental research (Ovadia 2014) while so called crowd-sourcing platforms enable the participation in the development of practical innovations with knowledge and labor (Estellés-Arolas and González-Ladrón-de-Guevara 2012).

Finally, for the individual being a private person digitalization allows to live more convenient and more self-determined with new technologies and services affecting various aspects such as communication, entertainment, learning, mobility, living as well as well-being, fitness and health. For example, with modern communication technologies (e.g. mobile telephones, wireless LAN, voice over IP, instant messaging services) communication is possible almost anywhere and at any time (Ling and Campbell 2017). Personal entertainment is individualized through TV streaming providers such as Netflix as they supersede linear TV programs (McDonald 2016). The same holds true for music streaming services such as Spotify or Apple Music. Furthermore, Massive Open Online Courses (MOOCs) such as Coursera enable people to learn outside of traditional school or university structures (Kizilcec et al. 2017) while the worldwide streaming of events such as music concerts (e.g. livelist) and operas (e.g. Operavision) allow a bigger audience to participate in cultural offers. Furthermore, new mobility concepts open easier and cheaper ways for transportation. With car sharing providers such as car2go, the need for a private car coming with various responsibilities of ownership is drastically reduced especially in urban regions (Remane et al. 2016). At home, the so-called smart home (e.g. intelligent lighting, heating, home security, energy management, etc.) emerged in recent years, boosted by voice-controlled smart speakers as a hub for information and device control (e.g. Google Home, Amazon Alexa) (Bugeja et al. 2016).

In addition, digitalization increases the individual's possibilities for maintaining and promoting well-being, fitness and health. For example, online and mobile services support fitness activities and healthy nutrition, provide information on a healthy lifestyle as well as diseases and therapies (Higgins 2016). In addition, with the rise of wearable self-tacking devices in recent years another facet for convenience and self-determination in well-being, fitness and health emerged. Self-tracking devices allow users to continuously collect, store and analyze data about their condition and to initiate behavior changes based on this information on their own without the need for external consultation (Lupton 2014b). Further, while self-tracking has already been done prior to digitalization, e.g. handwritten for selected parameters (often weight), modern self-tracking devices conveniently collect data directly via different sensors (Swan 2012). Self-tracking devices are thus part of the "Internet of Things", a term which will be explained subsequently.

2.2. Internet of Things

The term „Internet of Things" (IoT), which came up with the RFID technology at the Massachusetts Institute of Technology in 1999, refers to everyday objects being transformed into smart objects that can understand and react to their environment (Kortuem et al. 2010). A precise definition does not exist since IoT relates to different simultaneously evolving technologies (Oberländer et al. 2018). Oberländer et al. (2018) point out that there are varying conceptualizations of the two defining dimensions communication and things. This results in a debate on which communication standards IoT is based on and how the identity and capabilities of smart things should be defined.

However, the technologies Radio Frequency Identification (RFID) and sensors are relatively consistently described as foundation of IoT. These technologies are part of the collection phase of IoT applications and enable the identification of physical objects and sensing of physical parameters such as location, temperature and movements (Atzori et al. 2010; Borgia 2014).

Building on these technologies, various application types emerge. Along with the various definitions of IoT, different classifications of application types are present. For example, Atzori et al. (2010) propose the five main application domains transportation and logistics, healthcare, smart environment, personal and social which are directly applicable or close to our current living habitudes as well as a futuristic domain with applications that are currently not yet available since the technologies and/or the societies are not ready for their deployment. The five application domains and relevant major scenarios are presented in Figure 1.

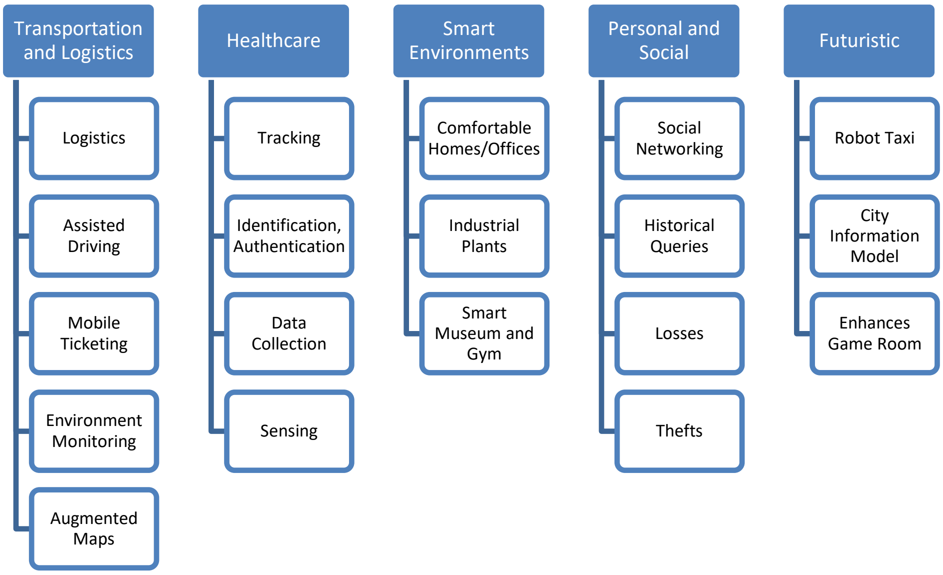

Figure 1: Application domains and relevant major scenarios adapted from Atzori et al. (2010).

In contrast, Borgia (2014) proposes a classification with the three main domains Industrial, Smart city and Healthcare which are further divided into subdomains and related applications. The complete classification is shown in Figure 2.

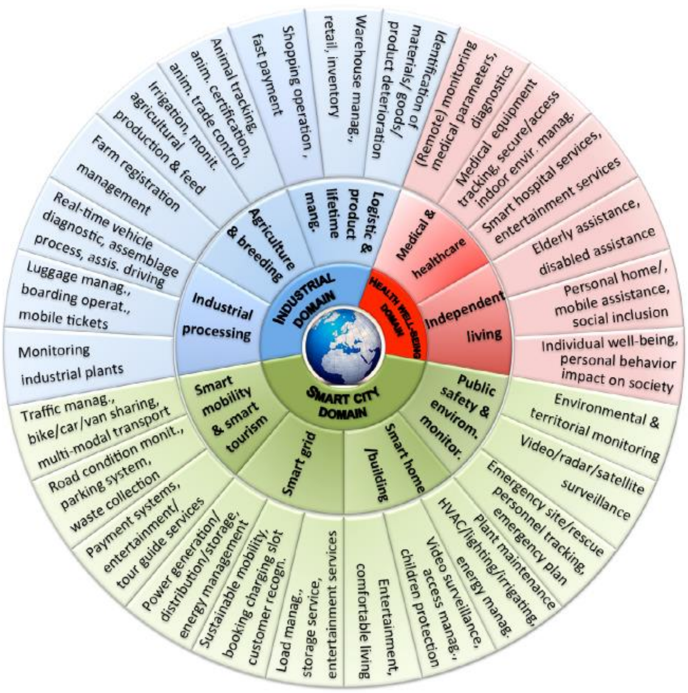

Figure 2: IoT application domains and related applications (Borgia 2014)

Concerning the research object of wearable self-tracking devices, this type of IoT-technology (Swan 2012) can be allocated best to the domain of healthcare in the classification of Atzori et al. or healthcare and well-being in the classification of Borgia respectively. Within the healthcare domain Atzori et al. describe the scenario “Sensing” as a “function centered on patients and in particular on diagnosing patient conditions, providing real-time information on patient health indicators” (2010, p. 9) for both, in-patient and out-patient care. This definition fits to the capabilities of current wearable self-tracking devices to monitor health-related conditions. An even better fit is given within the subdomain “Independent living” of Borgia’s classification. He describes well-being and lifestyle services which “will capture users’ habits to provide them suggestions to improve their quality of life” (2014, p. 11). This classification also comprises the capability of wearable devices to track fitness and well-being related data.

Having classified wearable self-tracking devices within the domain of IoT, development and characteristics of the technology will subsequently be explained in more detail.

2.3. Wearable Self-Tracking Devices

Due to the development of new tracking technologies and decreasing sensor sizes, self-tracking with wearable devices not only becomes increasingly convenient (Gimpel et al. 2013; Lupton 2014b), but also enables users to capture more and more aspects of their life. Nowadays, these devices enable users to capture various personal and even confidential data types, such as activities, exercises, vital parameters, disease symptoms, nutrition, among others (Gimpel et al. 2013; Pantzar and Ruckenstein 2015). With their broad tracking capabilities wearable self-tracking devices can serve as extensions of bodily senses. They enable their users not only to collect data about themselves, but also to interpret and to use this information to initiate changes in behaviors and habits (Kettunen et al. 2019a; Kettunen et al. 2019b; Lupton 2014b). Therefore, the nature of using such devices can be described to be more intense and personal than the usage of other consumer or business technologies.

Wearable self-tracking devices can be divided into two main categories according to IDC – basic and smart wearables. Smart wearables are defined by the ability to run third party applications, while basic wearables are limited to the software and ecosystem of the device manufacturer (Sawh 2017). Thus, the category of basic wearables comprises basic watches and wristbands, clothing, earwear and modular products while the category of smart wearables contains especially smart watches and smart wristbands (Mainelli 2018).

Basic wearables build the first generation of wearable self-tracking devices. The first devices of this generation emerged around 2008 with the FitBit Classic, followed by the Jawbone Up in 2011 and the Nike Fuelband in 2012 (Crawford et al. 2015). In contrast, smart wearables account for the second generation of self-tracking devices. They provide a platform for an entirely new and open ecosystem of applications and services both for new and traditional third-party providers, which can create additional value for the users beyond mere tracking and analysis of data (e.g. personalized sport and fitness support, dynamic health-insurances, and digital health-care support) (Lupton 2014a).

While shipments of mobile devices such as Notebooks, Tablets and Smartphones are predicted to stagnate or even decline (IDC 2019), wearable self-tracking devices still are an emerging technology with shipments rising from expected 125 million units in 2018 to 190 million units in 2022 (IDC 2018b). Separated by the categories basic and smart wearable, basic wearables account for the majority of sales both currently and for the next years, until smart wearables will take the lead by 2022. However, sales of basic wearables are predicted to continue rising.

Looking further at the different form factors of wearables, smartwatches and wristbands are predicted to account for the majority of shipments with over 95% market share in 2018 over devices such as smart clothing, earware or modular devices like clip-on tracker on the belt. Even tough total shipments for smartwatches and wristbands are expected to increase until 2022, IDC predicts a slight decline down to 88% market share due to an increase of clothing and earwear (IDC 2018b). The total forecasted shipments and market shares of wearable self-tracking devices in 2018 and 2022 are presented in Table 1.

Table 1: Forecast of shipments and market share of wearable self-tracking devices in 2018 and 2022 by category (adapted from IDC (2018b))

Product	**2018 shipments forecast in millions**	**2018 market share forecast**	**2022 shipments forecast in millions**	**2022 market share forecast**
Clothing	2.8	2.2%	9.1	4.8%
Earwear	2.1	1.7%	12.8	6.8%
Modular	0.7	0.6%	0.6	0.3%
Other	0.2	0.2%	0.2	0.1%
Watch	72.8	58.2%	120.2	63.3%
Wristband	46.5	37.1%	47.0	24.7%
Total	**125.3**	**100.0%**	**189.9**	**100.0%**

Concerning wearable self-tracking device manufactures, by the third quarter of 2018 the five biggest were Xiaomi (e.g. Mi Band), Apple (Apple Watch), Fitbit (e.g. Versa, Charge 3), Huawai (e.g. TalkBand B5) and Samsung (e.g. Galaxy). These five manufacturers account for more than 50% of the total market (IDC 2018a). The total distribution of market shares is shown in Table 2.

Table 2: Market shares for wearable self-tracking devices by the third quarter of 2018 (adapted from IDC (2018a))

Company	Market share by the third quarter 2018
1. Xiaomi	21.5%
2. Apple	13.1%
3. Fitbit	10.9%
4. Huawei	5.9%
5. Samsung	5.6%
Top 5 total	57.0 %
Others	43.0%
Total	**100.0%**

Conclusively it can be said that the rising sales for wearable self-tracking devices, the rapid development of the underlying technologies, the ongoing differentiation of device types and the involvement of major players of the consumer electronic market predict the importance of this technology in the future. It is thus most likely not only a temporary phenomenon but a sustainable technology that will become a part of the digitalized individual.

3. Research Questions and Conceptual Development

To address the goal of this dissertation to empirically investigate the usage behavior of wearable self-tracking devices it is fundamental to consider the technology adoption process in order to understand the factors that lead to the initial and continuous acceptance of a technology. In this regard the timeframe from the users' initial confrontation of a certain technology until the start of regular and continuous usage is defined as the acceptance phase of a technology (Sorgenfrei et al. 2014). The analysis of relevant factors of this initial phase is thus the first step to understand the usage behavior of wearable self-tracking device users. Following the acceptance phase, the post-acceptance phase covers the time of regular and continuous usage by the users (Sorgenfrei et al. 2014). The analysis of factors that keep users engaged is thus the second step that contributes to the understanding of the usage behavior. Furthermore, additional aspects such as effective use and motivations have to be taken into account to get a comprehensive overview of the usage behavior (Sorgenfrei et al. 2014). Effective use is defined as "using a system in a way that helps attain the goals for using the system" (Burton-Jones and Grange 2013, p. 633). In this regard, the disclosure of self-tracking data by users is necessary to facilitate the true potential of wearable self-tracking devices. The third step therefore will be to be better understand the data disclosure and privacy attitude of wearable self-tracking device users. Lastly, in addition to the perceptions of or attitudes towards wearable self-tracking devices, personal motivations of usage have to be considered within the adoption process (Sorgenfrei et al. 2014). Therefore, the fourth and final step towards the understanding of the usage behavior will be to analyze the underlying effects of motivation for self-tracking and the possibilities to influence them through the concept of gamification.

Based on this general structure, the motivations for and the derivation of research questions will subsequently be explained in more detail.

Step 1: Acceptance of wearable self-tracking devices

Concerning the understanding of the initial acceptance of a technology, key research has been conducted by Davis (1985, 1989) who developed the Technology Acceptance Model and its successor model as well as Venkatesh et al. (2003; 2012) who developed the Unified Theory of Acceptance and Use of Technology (UTAUT) and its successor theory. Within current acceptance model adaptions in the context of consumer systems, perceived usefulness, perceived ease of use and perceived enjoyment have been proven to be key predictors for acceptance (Bruner and Kumar 2005; Kulviwat et al. 2007; Lu et al. 2005; Venkatesh et al. 2012).

Furthermore, Gimpel et al. (2013) discovered several motivational factors for the practice of self-tracking, which range from hedonic purposes (e.g. self-entertainment) to utilitarian applications (e.g. self-discipline or self-healing). Gimpel et al.'s (2013) findings thus suggest that a wearable self-tracking device can have both a hedonic and utilitarian purpose. Hence, to be able to design product features which satisfy customer demands, manufactures need to know to what extent hedonic and utilitarian factors affect the intention to use wearable self-tracking devices. Therefore, the following first research question will be answered:

RQ1: What is the influence of utilitarian and hedonic factors on the intention to use wearable self-tracking devices?

In addition, wearable self-tracking devices are used to track, analyze and ultimately improve certain aspects of one's life, mostly in the categories well-being, fitness and health (Baumgart and Wiewiorra 2016; Gimpel et al. 2013). Hence, it can be assumed that customers appreciate system features of their wearable self-tracking device that offer perceived support in these three categories. However, it is unexplored how these three features determine the utilitarian and hedonic acceptance factors previously mentioned. Therefore, the following second research question will be answered:

RQ2: How does the support of specific self-tracking features influence utilitarian and hedonic acceptance factors?

To answer research question 1 and 2 a dedicated research model based on the technology acceptance model (TAM) (Davis 1985, 1989), the model of user acceptance of hedonic information systems (van der Heijden 2004) and previous research with a focus on various facets of the acceptance phase of wearable self-tracking devices (Chuah et al. 2016; Kim and Shin 2015; Lee and Lee 2018; Mercer et al. 2016; Sol and Baras 2016; Spagnolli et al. 2014; Xiaojun Wang et al. 2015; Yang et al. 2016) is developed to analyze the influence of utilitarian and hedonic factors on the intention to use wearable self-tracking devices. In addition, three new self-tracking specific constructs (perceived support of health, perceived support of fitness and perceived support of well-being) are added to the model and analyzed concerning their influence on the utilitarian and hedonic factors.

Step 2: Post-acceptance of Wearable Self-Tracking Devices

The post-acceptance phase is particularly important for new digital and traditionally "offline service providers, such as physicians and health insurance companies, which can create additional value beyond the pure tracking and analysis of data for the users and revenue for themselves over time (e.g. personalized sport and fitness support, dynamic health-insurances, and digital health-care support). These service providers have in common that associated business and service models rely on the continuous supply with data recorded by the basic technology – the wearable self-tracking device. Consequently, for the success of these applications and services, it is necessary that the self-tracking device fosters the users' continuance intention, while at the same time inhibiting the formation of a discontinuance intention in order to secure regular and ongoing usage after the initial acceptance.

Key research for the post-acceptance phase has for example been conducted with a focus on business technologies (Bhattacherjee et al. 2008; e.g. Bhattacherjee and Lin 2017; Furneaux and Wade 2011, 2017; Recker 2016) and business-consumer technologies (e.g. Bhattacherjee 2001; Chen et al. 2012; Cheung and Limayem 2005; Gong et al. 2018; Islam et al. 2017; Limayem et al. 2007; Limayem and Cheung 2008; Lin et al. 2014; Lin et al. 2017; Maier et al. 2015; Thong et al. 2006; Turel 2016; Vatanasombut et al. 2008; Venkatesh et al. 2011; Zhou 2013; Zhou et al. 2018). However, in contrast to the context of wearable self-tracking devices which process highly personal data and may initiate changes, emotions, and new habits, these research papers address continuance and discontinuance decisions in contexts which have a less intense personal connection to the users. Consequently, the results are of limited comparability. Furthermore, these research papers lack a comprehensive dual-factor view of continuance and discontinuance, even though previous research has shown that users can have both, enabling and inhibiting perceptions simultaneously (Park and Ryoo 2013). Corresponding research has been conducted with a focus on fitness trackers, smartwatches and wearable health devices (Becker et al. 2017a; Nascimento et al. 2018; Rockmann et al. 2018; Shen et al. 2018). However, these research studies either follow a qualitative approach or focus on certain matters of detail (e.g. type of device) and also lack of a comprehensive big picture. Therefore, to get this comprehensive view of the post-acceptance usage behavior in the context of self-tracking, the following research question will be answered:

RQ3: What determines continuance and discontinuance behavior of wearable self-tracking devices as a strong personal connection technology?

To answer the third research question several post-acceptance models such as Polites and Karahanna (2012), Limayem et al. (2007), Furneaux and Wade (2011), Bhattacherjee (2001) and Recker (2014, 2016) were adapted to a comprehensive dual-factor continuance and discontinuance model in the context of wearable self-tracking devices. In detail, the effect of five hygiene factors (negative social influence, system unreliability, system capability shortcomings, perceived routine constraints and trust) on the discontinuance intention and the effect of five enabling factors (perceived cognitive-based inertia, perceived affective-based inertia, perceived sunk costs, positive social influence and perceived usefulness) on the continuance intention are analyzed.

Step 3: Disclosure of Highly Personal Self-Tracking Data

While the abovementioned research questions analyze relevant acceptance and post-acceptance factors within the adoption process of a wearable self-tracking device, the subsequently described fourth research question addresses the users' privacy attitude towards disclosing highly personal self-tracking data.

Motivated by the latest generation of wearable self-tracking devices which offer a software and hardware ecosystems with open APIs, new digital as well as traditionally "offline" service providers, such as physicians and health insurance companies, are now enabled to offer new data-driven services based on the users' self-tracking data. However, without the users' agreement to share their personal self-tracking data, the service providers cannot (fully) deliver data-driven services. Thus, the continuous willingness of users to disclose personal data gathered through a self-tracking device is essential for the success of data-driven services.

In this regard, previous research has shown that users tend to unconsciously accepting terms and conditions about their privacy disclosure (Buck et al. 2014; Kim 2016). This means users are not always aware of the extent of private information disclosure (Stutzman et al. 2013). Previous research, however, has also shown that the willingness to disclose personal data also depends on the degree of data sensitivity (Horne, Daniel R. and David A. Horne 1998; Malhotra et al. 2004; Phelps et al. 2000). In addition, within a health context, previous research has shown that first, individuals display a high degree of data sensitivity and perceive high privacy risks and privacy concerns with regard to their health data (Anderson and Agarwal 2011; Caine and Hanania 2013; Li et al. 2016; Rohm and Milne 2004). Second, that individuals have different levels of privacy concerns (Rohm and Milne 2004) and sharing preferences (Caine and Hanania 2013) across different recipients.

Therefore, the self-tracking context is comparable with the health context in terms of data sensitivity, privacy risks and privacy concerns, since personal health, fitness and well-being data is processed. In contrast, the self-tracking context differentiate itself from the health context by new and unique characteristics of self-tracking users to engage in the processing of their data. In this regard, digital self-tracking devices are relatively new consumer products that are mostly voluntarily and consciously adopted by their users due to different personal motivations (Gimpel et al. 2013). Furthermore, these devices are used to get self-determined and convenient insights into one's bodily conditions and ultimately allow to self-initiate changes in behaviors and habits (Gimpel et al. 2013; Kettunen et al. 2019a; Kettunen et al. 2019b; Lupton 2014b). These "consumer device" usage characteristics thus define a unique context, that should be analyzed separately. Since the research base for highly personal data disclosure and privacy within the context of self-tracking is still scarce (e.g. Becker et al. 2017b; Becker 2018; Seifert et al. 2018; Wieneke et al. 2016; Zhang et al. 2015) and does not consider the calculus of personal risks and benefits of data disclosure with regards to data sensitivity and sharing preference, the following research question will be addressed:

RQ4: How does the calculus of personal risks and benefits influence the willingness of a user to disclose highly personal self-tracking data with regards to the data sensitivity and sharing preference?

To answer the fourth research question, a research model that is based on the comprehensive APCO Macro Model (Antecedents, Privacy Concerns, Outcomes) of Smith et al. (2011) with focus on the link between the privacy calculus (privacy risks versus financial rewards and service improvement benefits) and respective behavioral reactions is developed. To contribute to the specific context of self-tracking the two contextual factors data sensitivity and sharing preference between different data recipients are considered. Concerning data sensitivity, a distinction is made between activity data as a proxy for weak data sensitivity and health data for strong data sensitivity. In terms of the sharing preference, the focus solely lies on traditionally "offline" service providers since they provide an interesting near-future scenario (Bucher 2017; My Doctor Medical Group 2019). In detail, health insurance companies are considered as a proxy for a low sharing preference and family physicians for a high sharing preference. In addition to contextual factors, perceived activity condition and perceived health condition of self-tracking device users are taken into consideration as moderators in the research model, since previous research has shown that patients perceiving their health condition as poor are more sensitive about their health data than others (Bansal et al. 2010; Tisnado et al. 2006). By combining the contextual factors sharing preference and data sensitivity four groups are differentiated. In conclusion, the four groups are then analyzed and compared.

Step 4: Interplay of Motivations, Usage and Motivation Fulfillment

Finally, the conclusive two research questions complement the previously proposed research questions, since they do not address perceptions of or attitudes towards the technology and associated services but focus on the users' underlying motivations to engage in the practice of self-tracking.

Personal motivations influence individual behavior during both the acceptance and the post-acceptance phase (Sorgenfrei et al. 2014). It is thus important for manufacturers and service providers to better understand initial motivations, their evolution during the adoption process and ultimately perceived motivation fulfillment through usage of wearable self-tracking devices, in order to be able to tailor their devices and data-driven services accordingly. Previous research in this regard has shown that users act based on various motivations when they initially engage in different kinds of self-tracking activities (Baumgart and Wiewiorra 2016; Gimpel et al. 2013). However, it is still unanswered to which extent the users' initial motivations are actually fulfilled within the post-acceptance phase through the practice of self-tracking. Thus, the following research question will be answered:

RQ5: How does the usage of wearable self-tracking devices influence the user's perceived fulfillment of the initial motivations?

Furthermore, in the context of self-tracking motivations and motivation fulfillment, the practice of gamification should also be considered. Gamification describes the idea of using game design elements in non-game contexts (Deterding et al. 2016). It is a powerful method for motivating and influencing people (Bunchball Inc. 2010) and has the potential to change the users' behaviors (Lister et al. 2014). Gamification elements such as rewards, levels, leaderboards, goal-setting, and feedbacks are attributed to facilitate the attractiveness of monotonous physical activities (Rapp et al. 2012) and therefore motivate users to become more active (Zuckerman and Gal-Oz 2014). In this regard, the implementation of gamification elements could be a valuable tool for manufacturers and service providers to keep users engaged in the self-tracking practice. However, it is still unexplored how the usage of gamification elements interacts with different motivations to engage in self-tracking. Thus, the following research question will be answered:

RQ6: How does the usage of gamification elements within the wearable self-tracking device influence the interplay of self-tracking motivations, wearable self-tracking device usage, and motivation fulfillment?

To answer research questions 5 and 6, a conceptual model based on the research models of Gimpel et al. (2013) as well as Baumgart and Wiewiorra (2016) is analyzed. In this regard, the influence of the motivational factors as described in the five-factor framework on self-tracking usage (Gimpel et al. 2013) and ultimately the influence of usage on motivation fulfillment is investigated. In addition, gamification usage is integrated as a moderator to test its effect on the interplay of self-tracking motivations, wearable self-tracking device usage, and motivation fulfillment.

4. Research Structure, Method and Results

After having outlined the different research questions and conceptual developments, I will subsequently explain both research structure and method that have been used to answer the research questions and present key results of each analysis.

4.1. Research Structure

Concerning the research structure, four separate research essays form a cumulative approach to answering the introduced research questions. In detail, Essay 1 is dedicated to analyzing which factors lead to the initial acceptance of a wearable self-tracking devices (RQ 1+2). Furthermore, Essay 2 analyzes which factors promote the continuance intention, and which factors foster the discontinuance intention of wearable self-tracking device usage in the post acceptance phase, respectively (RQ3). Thus, both essays give a first comprehensive overview of the adoption process. In addition, two additional essays focus on specific topics associated with wearable self-tracking devices. Essay 3 refers to the privacy attitude of wearable self-tracking device users. It is analyzed which factors foster and inhibit the willingness to disclose personal self-tracking data to health insurance companies or family physicians based on the privacy calculus theory (RQ4). Finally, complementing the research of perceptions about the characteristics of the self-tracking technology and its usage, Essay 4 focuses on the fundamental motivations of self-tracking users to engage in this practice. Therefore, the interplay of motivations, usage and motivation fulfillment as well as the impact of utilizing gamification elements is analyzed (RQ 5+6). Towards the completion of the four essays, several development iterations have been presented at international scientific conferences and are now partly under review for journal publication. Table 3 gives an overview on the publication history of the research essays.

Table 3: Publication overview of research essays

Essay	Title	Publication History	Status	VHB JQ3 Ranking
1	Between fun and function: Identifying key acceptance factors for wearable self-tracking devices	Communications of the Association for Information Systems **Previous version:** Twenty-Fourth European Conference on Information Systems (ECIS), Istanbul, Turkey, 2016	Under review Published	C B
2	Insights into the Usage Behavior of the Digitalized Individual: Understanding Continuance and Discontinuance of Wearable Self-Tracking Devices	Information and Management **Previous version:** Twenty-Sixth European Conference on Information Systems (ECIS), Portsmouth, England, 2018 **Previous version:** 36th International Conference on Information Systems (ICIS), Fort Worth, USA, 2015 (Research in Progress)	Under review Published Published	B B A
3	The New Age of Data-Driven Services – Investigating Drivers and Inhibitors of the Willingness to Disclose Personal Self-Tracking Data	Business & Information Systems Engineering **Previous version:** 52nd Hawaii International Conference on System Sciences (HICSS), Maui, USA, 2019 **Previous version:** Twenty-Fifth European Conference on Information Systems (ECIS), Guimaraes, Portugal, 2017 (Research in Progress)	Under review Published Published	B C B
4	Self-Tracking and Gamification: Analyzing the Interplay of Motivations, Usage and Motivation Fulfillment	14. Internationale Tagung Wirtschaftsinformatik (WI), Siegen, Germany, 2019	Published	C

4.2. Research Method

A solid foundation of research models and constructs to explain usage behavior is available, on which the proposed research models in the context of wearable self-tracking devices are grounded. Hence, a quantitative research approach was consistently preferred over a qualitative research approach, following the goal to receive quantifiable and generalizable results.

In this regard, online surveys were used to collect quantifiable sample data. To do so, the software tool Qualtrics was applied to prepare and distribute the surveys. Since the surveys took place during the early phase of wearable self-tracking device diffusion, an open distribution approach had to be chosen. Although results are therefore threatened by a potential bias towards positive early adopters of wearable self-tracking devices, this was a necessary step in order to reach a sufficient quantity of participants that are aware of the technology or even have it in personal use already. Thus, participation invitations were posted or sent via online social networks (e.g. weblogs, Facebook wall postings, Facebook groups, and Twitter), online business networks (e.g. Xing and LinkedIn), the e-learning systems of the authors' universities and contacts of the authors. In addition, the platform Amazon Mechanical Turk was partly used since previous research has shown that it serves as a reliable source for data collection (Casler et al. 2013; Hauser and Schwarz 2016). The online surveys for the four essays took place at different points in time between early 2015 and early 2019.

To analyze conceptual and measurement models the structural equation modeling (SEM) approach partial least squares (PLS) was applied (Chin 1998; Wold 2004), using the software SmartPLS (Ringle et al. 2015). PLS-SEM was chosen as established approach in the IS research discipline (Gefen et al. 2011; Hair et al. 2011; Hair et al. 2017; Ringle et al. 2012).

To check for reliability and validity of the measurement models several quality criteria tests have been applied. In detail, internal consistency reliability was checked with the Cronbach's Alpha (CA) (Cronbach 1951) and the Composite Reliability (CR) (Bagozzi and Yi 1988; Chin 1998) approach. Furthermore, indicator reliability was assured by analyzing the outer loadings of all measurement items (Hair et al. 2014b). In addition, convergent validity was verified by analyzing the Average Variance Extracted (AVE) (Hair et al. 2014a) while discriminant validity was assessed using the Fornell-Larcker criterion (Fornell and Larcker 1981), the Heterotrait-monotrait (HTMT) approach (Henseler et al. 2015) and checks of cross loadings of the measurement items (Chin 1998).

4.3. Research Results

Following the previously introduced research structure, the key analysis results of each final essay version are briefly presented.

Results of Essay 1: Acceptance of wearable self-tracking devices

Key findings of this research essay with focus on the acceptance phase are that perceived usefulness and perceived enjoyment both have a significant effect on the intention to use wearable self-tracking devices. However, perceived usefulness of a wearable self-tracking device is the superior determinant of the intention to use wearable self-tracking devices compared to perceived enjoyment. In addition, surprisingly perceived ease of use neither showed a significant direct effect on the intention to use a wearable self-tracking device nor on the perceived usefulness of such device. However, a significant effect of perceived ease of use on perceived enjoyment was found.

Furthermore, the newly developed context specific variables perceived support of fitness and perceived support of well-being are significant determinants of perceived usefulness as well as perceived enjoyment. In contrast, perceived support of health only has a weak influence on perceived usefulness.

Results of Essay 2: Post-acceptance of Wearable Self-Tracking Devices

This research essay focusing on the post-acceptance phase revealed two key findings: First, new domain-specific factors which influence the continuance and discontinuance intention for a wearable self-tracking device were identified. Second, both enabling and inhibiting factors were found to simultaneously influence the usage behavior of self-tracking device users, thus confirming the dual-factor approach.

In detail, continuance intention is determined by the perceived usefulness of the wearable self-tracking device and the affective-based inertia of users. However, there is no effect of perceived cognitive-based inertia and perceived sunk costs by the users as well as positive social influence by one’s social group. Further, hygiene factors such as system unreliability and perceived routine constraints of the wearable self-tracking device, trust into the vendor and negative social influence by one’s social group determine the conscious formation of a discontinuance intention. In contrast, system capability shortcomings have no effect on the discontinuance intention.

Results of Essay 3: Disclosure of Self-Tracking Data to third parties

After analyzing four different groups concerning the sharing preference (health insurance company and family physician) and data sensitivity (weak data sensitivity for activity-related data and strong data sensitivity for health-related data), key findings are that privacy risks negatively and service improvement benefits as well as financial rewards positively influence the users' willingness to disclose personal self-tracking data in every group.

A more detailed analysis further revealed that the perceived activity as well as health status affect the impact of privacy risks on the willingness to disclose personal self-tracking data within the group of the family physician as the service provider. Further, within the group of the health insurance company as service provider and weak data sensitivity, a moderating effect of the perceived activity status on the relationship of service improvement benefits and the willingness to disclose personal self-tracking data was found.

Results of Essay 4: Interplay of Motivations, Usage and Motivation Fulfillment

Key findings of this essay with focus on the users' underlying motivations to engage in the practice are that the motivation for self-entertainment is the crucial driver of wearable self-tracking device usage. Furthermore, the usage behavior is then an important driver for the motivation fulfillment of self-entertainment, self-discipline, and self-design. Also, both the motivation as well as the motivation fulfillment are moderated by gamification usage respectively non-usage. Gamification users are more motivated by self-entertainment, non-gamification users more by self-design. In addition, the impact of usage on motivation fulfillment of self-discipline is significantly higher for non-gamification users than for gamification users.

5. Discussion of Results and Research Summary

5.1. Implications for Theory and Practice

Wearable self-tracking devices allow their users to collect and analyze data about their well-being, fitness and health and initiate positive behavior changes based on this information on their own without the need for external consultation. Thus, wearable self-tracking devices can be counted as a part of the digitalization of the individual since they contribute to the users' convenience and self-determination. However, to achieve these positive outcomes it is necessary that self-tracking device users initially accept and continuously use the devices, perceive motivation fulfillment through engagement in self-tracking, and are willing to disclose their personal self-tracking data to data-driven services.

The motivation of this dissertation was to analyze the usage behavior of wearable self-tracking device users. By investigating the acceptance and post-acceptance usage behavior and by considering privacy as well as motivational factors of users, a comprehensive overview on the usage behavior for wearable self-tracking devices is given. The research results provide both an extension of the theoretical knowledgebase for the highly personal and intense self-tracking context and dedicated recommendations for manufacturers and service providers how to design their products and data-driven services.

Concerning the acceptance phase (Essay 1), the research results show that the initial acceptance of wearable self-tracking devices is dependent on two design characteristics – being useful and being enjoyable. Also, the research on the newly introduced constructs perceived support of well-being, fitness and health further show that currently the support of fitness and well-being is in focus of users, while the support to deal with health-related issues has limited effect on their usage intention. A potential explanation therefor might be that current self-tracking devices only have limited functions to track health-related issues. However, with more sophisticated tracking options in the next generation of devices, the importance of support for dealing with health-related issues might increase.

For the subsequent post-acceptance phase (Essay 2) the results show that usage behavior is affected by continuance as well as discontinuance factors simultaneously. To inhibit discontinuance, several hygiene factors must be considered. In this regard, the new self-tracking-specific construct perceived routine constraints was introduced and appeared to be a significant determinant of discontinuance intention. Given that wearable self-tracking devices are closely connected to the users and often used all day long, sometimes even during sleep, it is necessary to provide a seamless and unobtrusive user experience to ensure convenience. Furthermore, with perceived usefulness and affective-based inertia being determinants of continuance intention, characteristics that have been important during the acceptance phase also remain important during the post-acceptance phase.

Concerning the privacy attitude of wearable self-tracking device users (Essay 3), the results show that the willingness to disclose self-tracking data to health insurance companies or family physicians is affected both by privacy risks and potential benefits – no matter whether activity data (e.g. fitness or well-being) or health data are subject to disclosure. Thus, to deliver services based on self-tracking data, service providers need to consider privacy risks perceived by users and should find ways to address them, for example by providing concrete information on how data security is ensured. The results further show that for users which perceive themselves as active or healthy, privacy risks have less negative influence on the willingness to disclose data to the family physician than for users which perceive themselves as less active or healthy. Hence, the effect of perceived activity or health status of the users should be considered by service providers, too. On the other hand, service improvement benefits and financial rewards foster the willingness to disclose personal self-tracking data. Thus, by offering benefits based on the users' self-tracking data, service providers could increase convenience and quality of their services as well as foster positive behavior of users (e.g. financial rewards for reaching a daily step count).

Finally, the research on underlying motivations of users to engage in the practice of self-tracking (Essay 4) revealed that self-entertainment is a key driver especially for those users leveraging gamification elements such as rewards, levels, leaderboards and challenges. Surprisingly though, the usage of wearable self-tracking devices not only fulfills the need for entertainment but also the need for self-design (i.e. gaining knowledge about interactions of certain things within their lives to be able to take control of and to optimize them) and self-discipline. For design and marketing of their devices and services manufacturers and service providers should consider, though, that users might not necessarily start self-tracking with the intention of self-design or self-discipline but seem to achieve motivation fulfillment for those previously unknown motivations when they become active wearable self-tracking device users.

5.2. Limitations

Due to the chosen research design and methodology as well as the period of time in which this research has been conducted, the four essays face certain limitations which could be overcome in future research.

At first, the research has been conducted during the initial rise of wearable self-tracking devices with only little research on this technology available. Therefore, the focus is on rather broad conceptional models since the authors regarded them as more valuable to gain a comprehensive understanding during the early stages of the technology. Furthermore, all four essays rely on a quantitative research approach, seeking to generalize predefined aspects of usage behavior for wearable self-tracking devices. However, this approach entails that other aspects have not been considered or were even not discovered. Future research could narrow down the focus on specific aspects such as demographic or characteristic attitudes of users with quantitative but also qualitative research approaches and thus further refine the knowledge of usage behavior for wearable self-tracking devices.

Second, due to the limited time wearable self-tracking devices have been available on the consumer market, especially with regard to the second generation of devices, the actual usage time of users and the availability of the ecosystem is limited. Thus, it can be assumed that the research samples have been influenced by first movers and early adopters of the technology who most likely have a slightly more positive attitude towards the technology. With the future diffusion of the technology to the majority of people the results of studies might differ, thus opening up future research opportunities to reevaluate the results presented in this dissertation.

Third, certain service benefits of wearable self-tracking devices such as data sharing with the health insurance company or family physician are still in their infancies and have not been used by a broad group of users yet. In essay 3, which is focusing on the disclosure of self-tracking data to third parties the research results are therefore based on hypothetical settings which were presented to the sample groups. Since users might behave differently given a hypothetical setting versus a real case situation, results might be a first indicator but should be reevaluated as soon as these service benefits are available to a broad group of users.

5.3. Outlook

While the technology of wearable self-tracking devices constantly develops, these devices will presumably further contribute to the digitalization of the individual in terms of increasing convenience and self-determination through both new or enhanced sensors capabilities and new data-driven services. When developing the research essays for this dissertation, self-tracking devices evolved from simple wristbands with only limited tracking functions (e.g. general activity, steps, calories) and few possibilities to connect and share data with others, to complex smartwatches which enable complex and accurate tracking (e.g. of the heartrate) and build the base for a new ecosystem of data-driven services. The next step will be further enhanced devices with even more accuracy and tracking opportunities especially for health-related parameters as well as data sharing possibilities.

A glimpse into this future is for example the Apple Watch Series 4 which is able to record an electrocardiogram (ECG) and then checks the recording for atrial fibrillation (AFib). This application is approved by the US Food and Drug Administration (FDA) and its data can be shared with the physician (Apple 2019). Coming iterations of self-tracking devices will most likely continue the transition from a simple data tracker to a serious health care device. Along with the new technical developments, wearable self-tracking devices will become more common and outgrow the application field of solely personal use. With the beforementioned development of serious health care tracking functions, the devices could complement traditional disease treatment, thus enabling more convenient, reliable and faster health care services. Already today first physicians in the US started to offer such services (My Doctor Medical Group 2019). Going beyond the treatment of diseases, preservation of health also is a growing topic. Based on self-tracking data, specialized digital platforms already offer training programs for various well-being, fitness and health related activities (e.g. Bell 2019) while traditional health insurance companies started to offer bonus programs for their members, providing monetary or non-monetary benefits for healthy behavior (e.g. reaching a certain amount of steps per day) (e.g. Bucher 2017). One step further, wearable self-tracking devices may also find their way into their users' work environments, thus affecting the digitalization of businesses. With the desire of employers to preserve a healthy and thus productive workforce, self-tracking related, often competitive initiatives aim to promote awareness for health and fitness thus complementing traditional workplace health management (Oesterle et al. 2019).

6. References

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7. Appendix

7.1. Declaration of Co-authorship and Individual Contribution

The presented research essays have been written as team projects with several co-authors. Subsequently I will explain the contributions of each author to the essays.[1]

Essay 1: Between fun and function: Identifying key acceptance factors for wearable self-tracking devices

I co-authored this essay with Jurij Pfeiffer, Nils Urbach and Arne Buchwald. The co-authors contributed as follows:

Jurij Pfeiffer (co-author)

Jurij Pfeiffer contributed by initiating, developing, and elaborating the entire research project. He conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. Thus, Jurij's co-authorship is reflected in the entire research project.

Matthias von Entreß-Fürsteneck (co-author)

I contributed by initiating, developing, and elaborating the entire research project. I conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. Thus, my co-authorship is reflected in the entire research project.

Nils Urbach (co-author)

Nils Urbach supervised the research project and provided mentorship. He contributed by engaging in the research idea development and textual elaboration. Further, he provided feedback to the research model, article structure and textual elaboration.

Arne Buchwald (co-author)

Arne Buchwald supervised the research project and provided mentorship. He contributed by engaging in the research idea development and textual elaboration. Further, he provided feedback to the research model, article structure and textual elaboration.

[1] Signed copies declaring the authors' individual contributions have been submitted with this thesis. This section's content was translated from these German original documents.

Essay 2: Insights into the Usage Behavior of the Digitalized Individual: Understanding Continuance and Discontinuance of Wearable Self-Tracking Devices

I co-authored this essay with Arne Buchwald, Albert Letner and Nils Urbach. The co-authors contributed as follows:

Arne Buchwald (co-author)

Arne Buchwald supervised the research project and provided mentorship. He contributed by engaging in the research idea development and textual elaboration. Further, he provided feedback to the research model, article structure and textual elaboration.

Albert Letner (co-author)

Albert Letner contributed by initiating, developing, and elaborating the entire research project. He conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. Thus, Albert's co-authorship is reflected in the entire research project.

Nils Urbach (co-author)

Nils Urbach supervised the research project and provided mentorship. He contributed by engaging in the research idea development and textual elaboration. Further, he provided feedback to the research model, article structure and textual elaboration.

Matthias von Entreß-Fürsteneck (co-author)

I contributed by initiating, developing, and elaborating the entire research project. I conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. Thus, my co-authorship is reflected in the entire research project.

Essay 3: The New Age of Data-Driven Services – Investigating Drivers and Inhibitors of the Willingness to Disclose Personal Self-Tracking Data

I co-authored this essay with Arne Buchwald and Nils Urbach. The co-authors contributed as follows:

Matthias von Entreß-Fürsteneck (leading co-author)

I contributed by initiating, developing, and elaborating the entire research project. I conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. Thus, my leading co-authorship is reflected in the entire research project.

Arne Buchwald (subordinate co-author)

Arne Buchwald supervised the research project and provided mentorship. He contributed by engaging in the research idea development and provided feedback to the research model, article structure and textual elaboration.

Nils Urbach (subordinate co-author)

Nils Urbach supervised the research project and provided mentorship. He contributed by engaging in the research idea development and provided feedback to the research model, article structure and textual elaboration.

Essay 4: Self-Tracking and Gamification: Analyzing the Interplay of Motivations, Usage and Motivation Fulfillment

I co-authored this essay with Henner Gimpel, Niclas Nüske, Timon Rückel and Nils Urbach. The co-authors contributed as follows:

Henner Gimpel (co-author)

Henner Gimpel supervised the research project and provided mentorship. He contributed by engaging in the research idea development and textual elaboration. Further, he provided feedback to the research model, article structure and textual elaboration.

Niclas Nüske (co-author)

Niclas Nüske contributed by initiating, developing, and elaborating the entire research project. I conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. He further supervised the research project and provided mentorship. Thus, Niclas' co-authorship is reflected in the entire research project.

Timon Rückel (co-author)

Timon Rückel contributed by initiating, developing, and elaborating the entire research project. He conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. Thus, Timon's co-authorship is reflected in the entire research project.

Nils Urbach (co-author)

Nils Urbach supervised the research project and provided mentorship. He contributed by engaging in the research idea development and textual elaboration. Further, he provided feedback to the research model, article structure and textual elaboration.

Matthias von Entreß-Fürsteneck (co-author)

I contributed by initiating, developing, and elaborating the entire research project. I conducted the literature analysis, conceptualized and analyzed the research model, evaluated the results, and conducted the textual elaboration. I further supervised the research project and provided mentorship. Thus, my co-authorship is reflected in the entire research project.

Between fun and function: Identifying key acceptance factors for wearable self-tracking devices

Abstract

Self-tracking as a form of digitization of the individual using wearable devices has developed from a niche existence into a widespread trend. While interest in research and practice increases, little is known about the intention why individuals adopt such devices. Therefore, we deductively derive a theoretical model drawing upon the technology acceptance model, the model of user acceptance of hedonic information systems and adapt them to the domain of wearable self-tracking devices. We validate it by means of structural equation modeling using empirical survey data of 469 participants. We found perceived usefulness to be the superior determinant of the usage intention compared to perceived enjoyment and perceived ease of use and also identified the influence of context-specific variables in terms of support of fitness, well-being, and health.

Keywords: Self-tracking, Quantified Self, Wearable Computing, Wearables, Wearable Self-tracking Devices, Information Systems Acceptance, Technology Acceptance, Digital Individual, Digitalization of the Individual, Smartwatches, Fitness Trackers.

Table of contents – Essay 1

1. Introduction

Self-tracking, also known as personal analytics or self-quantification has developed as a trend in the digitization of the individuals' private context. It refers to the activity of autonomously and freely monitoring and recording specific aspects of live (Lupton 2014c) by collection data about oneself, usually relating to health, fitness, or everyday habits and analyzing derived statistics, images, and diagrams (Choe et al. 2014; Sjöklint et al. 2015). Self-tracking technology consists of smartphones, wireless weight scales, blood pressure monitors, and so-called wearables such as smartwatches, wristbands, patches, clip-on devices and jewelry or textiles containing sensors, which digitally quantify an individual's bodily functions or physical activity (Lupton 2013b; Swan 2012b). Such wearable self-tracking devices continuously collect body metrics, like movement, heart rate, or calories burned (Gimpel et al. 2013; Lupton 2013a; Pantzar and Ruckenstein 2015). By analyzing the gathered data, they offer information services to improve personal health, fitness or well-being and with it customer satisfaction (Neuhofer et al. 2015).

It is expected that the distribution of wearable technology will surpass 190 million units by 2022 (IDC 2018). According to market research, more and more people are attracted by the practice of self-tracking to keep track of certain features of their live, to enhance knowledge about their bodies (Crawford et al. 2015), to live healthier (ABIResearch 2013; Whooley et al. 2014), or to share specific information (e.g. calories burned or distance run) as content with others on social media platforms (Baumöl et al. 2016; Lupton 2017). In this young market development stage with new players, products and platforms constantly joining the market of wearable self-tracking technology, a still unsolved key question for producers and developers, but also researchers, is which system characteristics drive the acceptance of wearable self-tracking devices.

Within current TAM adaptions in the context of consumer systems, perceived usefulness, perceived ease of use and perceived enjoyment have been proven to be key predictors for acceptance (e.g. Bruner and Kumar 2005; Kulviwat et al. 2007; Lu et al. 2005; Venkatesh et al. 2012). Furthermore, van der Heijden (2004) showed that for hedonic information systems perceived enjoyment and perceived ease of use are stronger determinants of intentions to use than perceived usefulness. However, Gimpel et al. (2013) discovered several motivational factors for the practice of self-tracking, which range from hedonic purposes (e.g. self-entertainment) to utilitarian applications (e.g. self-discipline or self-healing). Gimpel et al.'s (2013) findings thus suggest that a wearable self-tracking device can have both a hedonic and utilitarian purpose. Hence, to provide customers a product that satisfies their demands, manufactures need to know to what extent hedonic and utilitarian factors affect the intention to use wearable self-tracking devices and to design the product features accordingly. We therefore want to answer the following first research question:

RQ1: What is the influence of utilitarian and hedonic factors on the intention to use wearable self-tracking devices?

In addition to the unknown influence of utilitarian and hedonic acceptance factors on the intention to use, we believe that these factors are also determined by technology-specific customer demands. As stated, wearable self-tracking devices are used to track, analyze and ultimately improve certain aspects of one's life, mostly in the categories fitness, well-being and health (Baumgart and Wiewiorra 2016; Gimpel et al. 2013). Hence, it can be assumed that customers appreciate system features, which offer perceived support in these three categories. However, it is by now unexplored how these specific features determine utilitarian and hedonic acceptance factors. We thus want to answer the following second research question:

RQ2: How does the support of specific self-tracking features influence utilitarian and hedonic acceptance factors?

To answer our research questions, we develop a theoretical model based on the technology acceptance model (TAM) (Davis 1985, 1989) and the model of user acceptance of hedonic information systems (van der Heijden 2004), and validate it drawing on a survey among 469 participants. We apply structural equation modeling, using the partial least squares (PLS) approach (Urbach and Ahlemann 2010) for the full sample.

In terms of theoretical contribution, our objective is to contribute to the acceptance research stream in two different ways. First, we want to analyze the system nature of wearable self-tracking devices by evaluating the influence of utilitarian and hedonic factors on the intention to use; second, we aim at providing insights into the effect of specific self-tracking features on the utilitarian and hedonic acceptance factors. In terms of implications for practice, self-tracking device manufacturers are equipped with knowledge on the product expectations of potential customers that can help them to design the device features accordingly.

Our paper is structured as follows. In Section 2, we discuss the relevant theoretical foundations concerning technology adoption, wearable self-tracking devices and their acceptance. Based on these foundations, we develop our hypotheses in Section 3. In Section 4, we outline our approach to collecting empirical data and to analyzing the measurement model. In Section 5, we assess the results of our structural models. Subsequently, we discuss our findings and practical implications in Section 6. Finally, in Section 7, we conclude the paper, discuss the limitations, and outline our suggestions for future research.

2. Theoretical Foundations

2.1. Technology Adoption

Previous research has extensively analyzed the adoption of information systems (IS) by investigating how individuals proceed through the adoption process of gathering information and knowledge, developing an attitude towards the technology, deciding on the acquisition, using the technology, and confirming the previously taken decision (Rogers 1983; Sorgenfrei et al. 2014). Several theories were developed to explain parts of the adoption process, all of which can be divided into an acceptance and post-acceptance phase (Cooper and Zmud 1990; Fichman 2001; Hameed et al. 2012; Sorgenfrei et al. 2014).

Theories rooted in the social psychology such as the theory of reasoned action (Fishbein and Ajzen 1975) and theory of planned behavior (Ajzen 1991; Ajzen and Madden 1986) have been the basis for succeeding research explaining the acceptance phase of information technology (IT). Following their underlying principal that future actions can be predicted on the basis of the perceptions about future consequences, models such as the technology acceptance model (TAM) (Davis 1989; Davis et al. 1989) or the innovation diffusion theory (Moore and Benbasat 1996) have been developed. Their key contribution is that perceived usefulness and perceived ease of use are relevant for explaining the behavioral intention or attitude of using a specific technology and reflect the utilitarian nature of human behavior. However, consumer behavior research argues that next to utilitarian, hedonic aspects can be of particular relevance for explaining the general intention to consume products (Babin et al. 1994; Hirschman and Holbrook 1982; Holt 1995; van der Heijden 2004). Subsequent research extended the original TAM by hedonic-oriented and other factors, resulting in the unified theory of acceptance and use of technology (UTAUT) (Venkatesh et al. 2003) and its extension (UTAUT2) (Venkatesh et al. 2012).

2.2. Wearable Self-Tracking Devices

Wearable self-tracking devices have the capability to measure and analyze highly personal and often confidential bodily data in regard to well-being, fitness and health (Gimpel et al. 2013; Pantzar and Ruckenstein 2015). Used all day long and often also during sleep the usage behavior of these devices is much more complex and intense than with other consumer technologies such as smartphones or mobile computers. Wearable self-tracking devices do not simply collect data, but also help paying attention to the self, potentially raise self-awareness and initiate changes in behaviors and habits (Kettunen et al. 2019a; Kettunen et al. 2019b; Lupton 2014c). In this sense, the character of such devices is not merely some human-machine interaction, but it is a reflexive one. Sociologists refer to this feature of self-tracking devices as the qualified-self (e.g. Davis 2013). The practice of collecting data is only one part in the concept of self-tracking. Self-tracking also includes interpretation and assessment of the collected personal data as well as the reconnection with other forms of data (Lupton 2014c). Self-quantifiers then use the collected personal data to construct stories that they tell themselves about themselves (Davis 2013). The mere act of wearing and using a self-tracking device or of positioning oneself as a self-tracker, is already an expression of a certain type of subject: the entrepreneurial, self-optimizing subject (Lupton 2014a). Thus, due to these complex interactions, we argue that the adoption process of wearable self-tracking devices differs compared to other consumer technologies and should therefore be analyzed separately.

2.3. Acceptance of Wearable Self-Tracking Devices

Only few studies so far have analyzed the technology adoption process regarding wearable self-tracking devices. While the post-acceptance phase (e.g. Becker et al. 2017; Nascimento et al. 2018; Rockmann et al. 2018; Shen et al. 2018) focuses on users already using a self-tracking device, we subsequently elaborate on relevant research of the acceptance phase for wearable self-tracking devices.

Summarized in respect to research related to smartwatches, perceived usefulness showed no significant direct effect on behavioral intention and requires behavioral attitude as an intermediary. A positive effect of perceived ease of use on attitude was also found (Chuah et al. 2016; Kim and Shin 2015), while the relationship between ease of use and behavioral intention was not considered. With respect to wearable fitness devices, this view changes with one study suggesting perceived usefulness as well as perceived ease of use to have a significant effect on behavioral intention to use (Sol and Baras 2016). In addition, the influence of ease of use is of special relevance for older people and users with a medical reason for acceptance (Mercer et al. 2016; Xiaojun Wang et al. 2015). A different study also identified perceived enjoyment, representing hedonic motivation, to have a positive effect on behavioral intention (Xiaojun Wang et al. 2015). Another study found that the intention to adopt was stronger among respondents who were aware of wearable fitness trackers than it was among those who were not aware. Also, consumer attitudes, personal innovativeness, and health interests have a positive effect on the intention to adopt (Lee and Lee 2018). In the domain of wearable devices in general, perceived usefulness and perceived ease of use were found to be good predictors of behavioral intention (Spagnolli et al. 2014). There, functionality and compatibility are of importance for explaining usefulness, while enjoyment is explained by visual attractiveness (Yang et al. 2016). The presented studies started to analyze which factors influence the acceptance of users and thus provide a good starting point for this study to further refine and expand the contextual understanding of acceptance of wearable self-tracking devices.

3. Conceptual Development

The specifically refined picture about technology acceptance – to the best of our knowledge – is not yet available in the self-tracking context, which is why we propose a conceptual model which builds on established theories and extend them by factors representing the context of wearable self-tracking devices. Accordingly, we add three self-developed variables that capture the perceptions as to what extent wearable self-tracking devices support fitness, health, and well-being objectives. Most self-tracking users track physical activities (e.g. exercise, steps walked), body traits (e.g. weight, heart rate), well-being (e.g. sleep cycles and quality), nutrition and medical issues (Appelboom et al. 2014; Gimpel et al. 2013; Rooksby et al. 2014; Swan 2009, 2012a). The ultimate goal of gathering more knowledge about one's body may comprise weight loss, steps walked, or any other goal related to well-being, health, and fitness (Lupton 2017). In the following model development, these three determinants are defined as distinct factors and are theorized to have a direct and positive effect on the perceived usefulness as well on the perceived enjoyment of wearable self-tracking devices.

Behavioral Intention to Use

Individual behavior is driven by a person's intention to perform the specific behavior (Hameed et al. 2012) which is why acceptance studies aim at explaining determinants that influence the behavioral intention. In line with previous acceptance models, we adapt the behavioral intention to use a technology as the dependent variable in our study. Following Fishbein and Ajzen (1975), we define the behavioral intention (BI) as a measurement of the strength of an individual's intention to use a wearable self-tracking device.

Perceived Usefulness

In the majority of previous TAM studies, Perceived Usefulness (PU) was shown to be one of the strongest determinants of technology acceptance (Kulviwat et al. 2007; Taylor and Todd 1995; Venkatesh et al. 2012). There, TAM conventionally analysis PU from an occupational perspective with a primarily focus on productivity, effectiveness and performance (Legris et al. 2003).

Recent studies also give reason to confirm PU's importance to explain acceptance in the domain of wearable computing in general and in self tracking in particular (Shin and Biocca 2017). In case of wearable self-tracking devices, we posit that most customers have specific purposes in mind that the device is supposed to usefully support, such as weight loss, being more active, health tracking, or simply to capture data, reflecting the utilitarian purpose (van der Heijden 2004). Therefore, we define perceived usefulness as the degree to which a wearable self-tracking device fulfills its intended usage purpose of the individual user and hypothesize:

Hypothesis 1: The perceived usefulness has a positive effect on the behavioral intention to use wearable self-tracking devices.

Perceived Enjoyment

Next to PU representing the utilitarian nature in acceptance processes, hedonic aspects are of particular relevance for explaining acceptance in the consumer context as well (van der Heijden 2004) by aiming for providing enjoyment to the user (Wu and Lu 2013; Zhang and Sun 2006). Therefore, devices and information systems in the consumer context typically contain enjoyment-oriented rather than productivity-oriented functions and have been found to be an important determinant for predicting the use of technology by customers in several studies (Bruner and Kumar 2005; Kulviwat et al. 2007; Venkatesh et al. 2012). Perceived enjoyment (PE) is defined as the degree to which "fun or pleasure [is] derived from using a technology" (Venkatesh et al. 2012, p. 161). As the usage of wearable self-tracking devices includes hedonic-oriented playful components such as "toying" around with data and competing with friends or online peers, we include this determinant in our research model (Xiaojun Wang et al. 2015). Thus, we hypothesize:

Hypothesis 2: The perceived enjoyment has a positive effect on the behavioral intention to use wearable self-tracking devices.

Perceived Ease of Use

Perceived ease of use (PEOU) in TAM is a variable to assess a person's individual believes in using a technology being free of effort (Davis 1985; Lin et al. 2007). We adopt the original explanation and define PEOU as the degree to which an individual believes that using a self-tracking device would be free of effort. PEOU was examined extensively, and a significant body of research supports the assumption that the easiness of a system is important for initial user acceptance and sustained usage of information systems (Schepers and Wetzels 2007; Venkatesh 2000). Therefore, we hypothesize:

Hypothesis 3a: The perceived ease of use has a positive effect on the behavioral intention to use wearable self-tracking devices.

In addition to the direct effect of PEOU on BI, past research also identified the importance of PEOU for the actual usefulness of information systems and devices. According to Legris et al. (2003), 21 out of 26 studies testing this relationship between PEOU and PU found a significant positive connection. Since wearable self-tracking devices can vary in handling from very simplistic to complex analysis tools for a person's data, users might also see this aspect as relevant for the device to be useful. Hence, we incorporate this notion in our model and hypothesize:

Hypothesis 3b: The perceived ease of use has a positive effect on the perceived usefulness of wearable self-tracking devices.

A so far less analyzed aspect in information systems research is the relevance of PEOU for the hedonic motivation and enjoyment associated with the device. Zhang and Sun (2006) reviewed existing literature analyzing this aspect and found five studies that all confirm this relationship. If user interfaces are difficult to handle and too complex, requiring sufficient mental effort in handling, the perceived enjoyment related to the device would reduce. We argue that an easy handling of wearable self-tracking devices is essential for users' hedonic motivation and, thus, hypothesize:

Hypothesis 3c: The perceived ease of use has a positive effect on the perceived enjoyment of wearable self-tracking devices.

Perceived Support of Fitness

We define perceived support of fitness (PSF) as the degree to which wearable self-tracking devices are perceived to support the individual in improving his or her fitness and sport activities. Wearable self-tracking devices are designed to support tracking and analyzing data concerning the individual fitness and sport (e.g. running or swimming) (Rooksby et al. 2014). Moreover, besides the distinct feature to analyze recorded data on their web or mobile platforms, most wearable self-tracking devices also set goals and provide motivation for the user as well as feature the possibility to compare and compete with close social peers or all users in the ecosystem. Thus, the devices include playful elements. We therefore argue that the fitness features do not only have a serious purpose with consequently a positive influence on the perceived usefulness, but also provide playful elements which, as a consequence, positively affect the perceived enjoyment of the device. Thus, we hypothesize:

Hypothesis 4a: The perceived support of fitness has a positive effect on the perceived usefulness of wearable self-tracking devices.

Hypothesis 4b: The perceived support of fitness has a positive effect on the perceived enjoyment of wearable self-tracking devices.

Perceived Support of Well-Being

We define perceived support of well-being (PWB) as the extent to which wearable self-tracking devices are perceived to support the individual's general mental and physical constitution. In contrast to perceived support of fitness, this determinant is not about keeping track of a particular type of fitness or sport activity but focuses more on the overall well-being as a mental state in terms of controlling common activities, for instance, steps walked, stand-up time during the day, or hydration (Rooksby et al. 2014). Wearable self-tracking devices offer a range of functionalities that may foster well-being in a very general way. Some devices can perform sleep analyses and reveal information about the quality of sleep, while others remind the user to be more active from time to time or to perform a deep breathing routine. Hence, they offer functions that foster the perceived usefulness of the device. As with perceived support of fitness, the devices also mostly offer the possibility to compare results and achievements with others, set goals and give motivation to the user, hence offering functions that facilitate enjoyment. Thus, in the same vain as with perceived support of fitness, we posit perceived support of well-being as antecedents of perceived usefulness as well as of perceived enjoyment and hypothesize:

Hypothesis 5a: The perceived support of well-being has a positive effect on the perceived usefulness of wearable self-tracking devices.

Hypothesis 5b: The perceived support of well-being has a positive effect on the perceived enjoyment of wearable self-tracking devices.

Perceived Support of Health

We define perceived support of health (PSH) as the degree to which wearable self-tracking devices are perceived to support the control and treatment of health-related issues. Various wearable self-tracking devices can capture data on the individual health status which might be valuable to doctors and physicians (e.g. heart rate and rhythm) as well as for users themselves, in order to be in control of the individual health status, independent from analyses and suggestions of doctors (Appelboom et al. 2014; Gimpel et al. 2013; Williams 2014). While a serious purpose and therefore an influence on perceived usefulness can be assumed, it is debatable whether a relationship to perceived enjoyment is also relevant in this context, since the focus is on the treatment of often serious health-related issues. However, we argue that the tracking, analysis and sharing of positive progress in the treatment of health-related issues can also be an enjoyable experience and therefore posit that the perceived support of health is an antecedent of perceived usefulness as well as of perceived enjoyment in the context of wearable self-tracking devices:

Hypothesis 6a: The perceived support of health has a positive effect on the perceived usefulness of wearable self-tracking devices.

Hypothesis 6b: The perceived support of health has a positive effect on the perceived enjoyment of wearable self-tracking devices.

Research Model

Summarizing, we primarily draw upon the acceptance theories of TAM and the model of user acceptance of hedonic information systems from van der Heijden (2004) and adapt them to the domain of wearable self-tracking devices by integrating three new context-specific variables. The final model consists of eleven hypotheses and is shown in Figure 1. Since we aim at understanding the key driver of acceptance of wearable self-tracking devices, we gathered beliefs of respondents who do not yet use such devices.

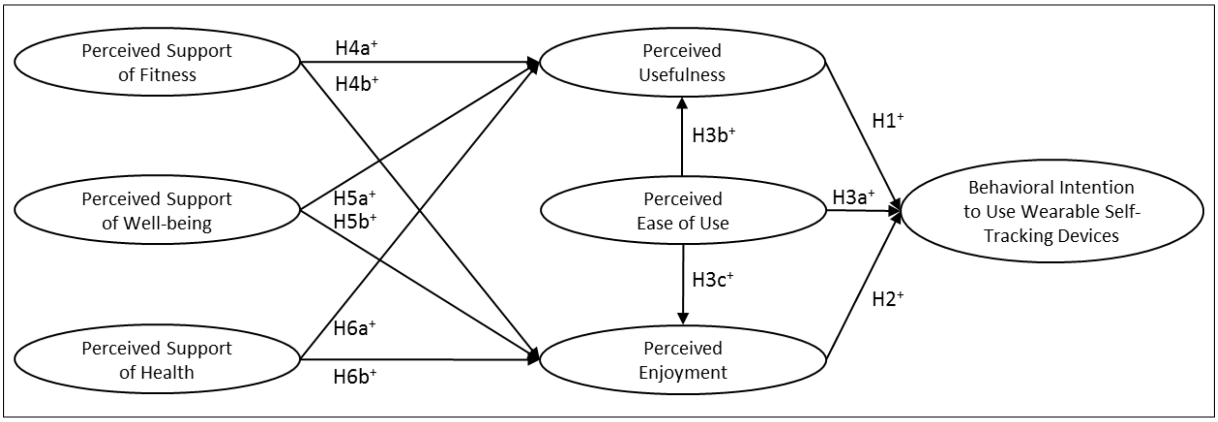

Figure 1: Proposed Conceptual Model

4. Empirical Data

We carried out an online survey to validate our conceptual model. We relied on established and proven scales as much as possible to enhance the validity as suggested by several authors (e.g. DeLone and McLean 2003). The specific items of our measurement instrument are shown in Appendix A. All variables were measured using reflective, seven-point Likert (from 1 indicating strong disagreement to 7 indicating strong agreement), multiple-item scales. Additionally, we collected demographic information, such as age and gender. The resulting questionnaire was reviewed for content validity by two other researchers. Additionally, we carried out a card-sorting procedure similar to the one adopted by Moore and Benbasat (1991) supported by an online tool (concept codify) to ensure that the scales are easy to understand and unambiguous. The questionnaire was finally pilot-tested by seven graduate students and five university staff members.

We sampled current *non-users* of wearable self-tracking devices to identify those decisive factors which lead to individuals developing a behavioral intention to use such technology. We excluded those people in the very beginning of the survey who already use or who used a self-tracking device in the past. To help reduce a non-response bias, the online survey included a comprehensive introduction encompassing the objective of our study, a definition of wearable self-tracking technology, and an assurance of anonymity. Furthermore, all participants were reassured that there were no right or wrong answers and that participants should answer using intuition or prior experience with similar technology. We decided to use a variety of distribution channels for the invitation to participate in our survey. These channels of the first data collection approach included online social networks, such as Facebook and Twitter, as well as student mailing lists of two German universities. In the second data collection approach, we leveraged

Amazon Mechanical Turk (AMT) to further extend the number of participants in our study. AMT has been used by researchers in a variety of domains, and its participants were found to "produce reliable results consistent with standard decision-making biases" (Goodman et al. 2013, p. 213).

5. Analysis and Results

Overall, we gathered 631 and 183 responses in the first and second approach, respectively, totaling 814 responses. After discarding all those who did not fully complete the online questionnaire, we obtained a sample of 500 responses. We further scrutinized our sample for multivariate outliers by applying mahalanobis distance and proceeded with a final sample of 469 responses in the analysis. The response rate cannot be computed because the total number of individuals who could have responded cannot be known for our whole sample. The average participant is 29.4 years old and the majority holds a university degree. 55% of the respondents are male.

Before proceeding to the structural analysis, we checked our measurement model for internal consistency, convergent validity, and discriminant validity. We analyzed Cronbach's Alpha (CA) and the Composite Reliability (CR) to test the internal consistency of our measurement instrument. All values exceed the threshold of 0.8 (Table 1), showing a high degree of internal consistency. Finally, we assessed the convergent and discriminant validity.

Table 1: Measurement Model's Results

Latent Variable	**CR**	**AVE**	**CA**
Behavioral Intention to Use Wearable Self-Tracking Devices (BI)	0.956	0.846	0.939
Perceived Usefulness (PU)	0.918	0.737	0.881
Perceived Enjoyment (PE)	0.942	0.804	0.918
Perceived Ease of Use (PEOU)	0.937	0.790	0.911
Perceived Support of Fitness (PSF)	0.900	0.695	0.852
Perceived Support of Well-Being (PWB)	0.950	0.863	0.920
Perceived Support of Health (PSH)	0.927	0.717	0.900
Notes: CR = Composite Reliability, AVE = Average Variance Extracted, CA = Cronbach's Alpha			

The Average Variance Extracted (AVE) is greater than the critical threshold of 0.5 for all constructs. Furthermore, we analyzed the indicator reliability. The outer loadings of all measurement items exceed the threshold of 0.708 (Hair, JR. et al. 2014). To assess discriminant validity, we applied the Fornell-Larcker criterion as a conservative measure (Fornell and Larcker 1981). The square root of each construct's AVE is greater than its highest correlation with any other construct (see Table 2). Further, we checked the cross loadings and all items have the highest loadings with the construct with which they are theoretically related (Appendix B). In addition to the traditional discriminant validity check, we applied the Heterotrait-monotrait (HTMT) approach (Henseler et al. 2015). All values are below 0.95 which is why we conclude that discriminant validity has been established.

Table 2: Correlations and Square Roots of AVE Values

	BI	PU	PE	PEOU	PSF	PSW	PSH
BI	0.920						
PU	0.736	0.859					
PE	0.614	0.673	0.897				
PEOU	0.124	0.120	0.192	0.889			
PSF	0.599	0.758	0.560	0.168	0.834		
PSW	0.705	0.775	0.639	0.109	0.708	0.929	
PSH	0.626	0.722	0.535	0.162	0.801	0.725	0.847

We assessed the structural model with partial least squares (PLS) structural equation modeling (SEM) using SmartPLS 3.2. (Ringle et al. 2015). We chose PLS-SEM as an established method in the IS research discipline (Gefen et al. 2011; Hair et al. 2011; Hair et al. 2017; Ringle et al. 2012) primarily for two reasons: First, we aim for predicting the key determinants of our salient variables that PLS-SEM better performs than CB-SEM as it maximizes the variance explained (Hair et al. 2017). Second, PLS-SEM, in comparison to plain maximum likelihood CB-SEM, can better deal with data (as in our case) that is not perfectly normally distributed (Hair et al. 2017) . To assess the significance levels, we applied bootstrapping with 5,000 sub-samples. The results are provided in Figure 2 encompassing path coefficients, significance levels, and R^2 value for the complete model without categorical moderating variable effects. Relating to our direct effects that we proposed, eight out of eleven hypotheses could be confirmed. A subsequent multi-group analysis with age and gender showed no significant differences to the overall sample group.

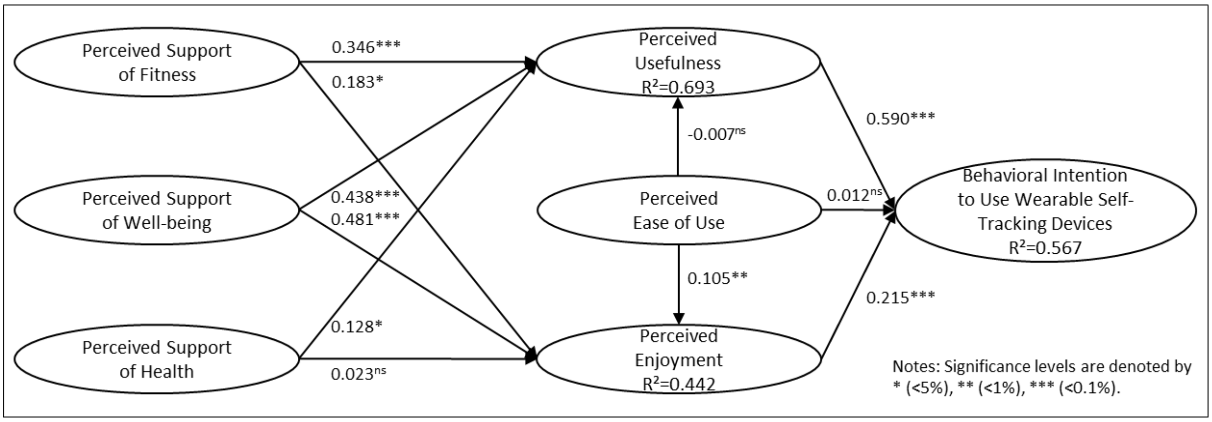

Figure 2: Assessment of the Structural Model

6. Discussion

Our results show that perceived usefulness as well as perceived enjoyment have both a significant impact on the intention to use wearable self-tracking devices, while perceived ease of use has no influence at all. Further, the relationship between perceived usefulness and the intention to use is stronger than the relationship between perceived enjoyment and the intention to use. Referring to our first research question, these results suggest that wearable self-tracking devices are perceived by non-users to be of utilitarian as well as hedonic nature. However, the results indicate a stronger relevance for the utilitarian-driven motivation and are thereby contradicting to van der Heijden (2004), who showed that perceived enjoyment and perceived ease of use are stronger determinants of intention to use a hedonic information system than perceived usefulness. Thus, wearable self-tracking devices should be seen primarily as serious tools, which have to fulfill certain support features for the customers in order to be beneficial while the enjoyment of the usage is subordinate. We therefore suggest a so-called “fun follows function”-strategy with the focus being mainly on developing and on promoting the usefulness of the tracking and analysis features.

Looking again at the results for perceived ease of use, it turns out to be only significant on perceived enjoyment in our sample. The insignificant relationship to perceived usefulness and the intention to use is surprising, given its importance in previous research on acceptance theories. A possible explanation may be rooted in the context of analysis in past studies. Mostly, PEOU was analyzed in a work-context in which complex information systems were used and an easy-to-handle graphical user interfaces (GUI) were actually recognized as useful, thus raising the acceptance. However, wearable self-tracking devices are usually controlled with simple smartphone applications that people expect to be effortless in handling (see, for instance, Agrebi and Jallais 2015; Lim et al. 2011; Slade et al. 2015). Since a complex usage environment is missing, PEOU cannot contribute to usefulness. This is supported by other studies, which found PEOU to be not significant in the field of smartphones usage for mobile shopping, mobile commerce, mobile banking, mobile payment and mobile learning (Agrebi and Jallais 2015; Chong 2013; Slade et al. 2015; Thomas et al. 2013; Yu 2012). Nonetheless, our results indicate that enjoyment actually increases with an effortless handling. An intuitive designed and simple GUI contributes to the user experience by enjoying the actual interaction with the device and its application. Manufactures are well advised to still consider an easy handling important, even if other studies show no relevance for PEOU in similar contexts.

In terms of our second research question, our results show that system features for fitness and well-being are not only valued by potential customers, but also determine both perceived usefulness as well as perceived enjoyment of the system. Hence, our results suggest that fitness and well-being features are perceived by potential customer to have both a serious purpose and a playful element. These are key elements, for which manufacturers can develop further feature sets. Especially the area of well-being currently offers only very few features for self-tracking users and thereby is a feature gap for manufacturers to close (for instance work-related or not fitness-related activities). In contrast, for perceived support of health, we found a significant but relatively weak influence on perceived usefulness compared to perceived support of fitness and perceived support of well-being and surprisingly no significant relationship with perceived enjoyment. The comparably weak effect of perceived support of health could be the consequence of the limited features current consumer-oriented wearable self-tracking devices offer. While they enable basic health-tracking capabilities, advanced analysis support and the possibility to share the data with experts is still scarce. Hence, we argue that perceived support of health is seen by potential customers more as a “nice to have”-addon than a key feature. Consequently, the capabilities to analyze health issues should be further improved to foster utilitarian-driven acceptance. Further, for the insignificant relationship with perceived enjoyment, a possible explanation might be that potential customers do not see how the tracking and analysis of health-issues could be enjoyable, since health is mostly seen as a serious matter. Hence, manufacturers are challenged to develop and to promote new ways how the tracking of health issues can also be enjoyable to further foster the overall perceived enjoyment and ultimately the intention to use of the devices.

7. Summary and Conclusion

Our objectives were to investigate the influence of utilitarian and hedonic factors on the intention to use wearable self-tracking devices as well as to identify how the support of specific self-tracking features influence these factors. Following Venkatesh et al.'s (2012) suggestion to refine generic acceptance theories to specific contexts, we developed an adapted acceptance model based on the prominent technology acceptance model (Davis 1985; Davis et al. 1989) and the model of user acceptance of hedonic information (van der Heijden 2004) specific to the self-tracking domain. In terms of our first research question, we identified perceived usefulness as the superior determinant of the intention to use compared to perceived enjoyment and perceived ease of use, which was surprisingly not significant at all. With a utilitarian factor being more important than hedonic factors, we suggest a "fun follows function"-strategy for manufactures. Concerning our second research question, we found perceived support of fitness and perceived support of well-being to be significant determinants of perceived usefulness as well as perceived enjoyment while perceived support of health has no influence at all. These results suggest, that the support of health is rather a "nice to have"-addon than a key feature to the product. While our research project aimed at advancing the current body of knowledge on acceptance theories specific to the self-tracking domain, we acknowledge two limitations that should be addressed by future research. First, we chose a convenience sampling approach and openly distributed the invitation to participate, as the only key selection criteria was related to sampling current non-users of wearable self-tracking devices. As such, we were not able to check for a potential non-response bias because we have no information on the group of people which could have responded to our questionnaire. Second, our study does not analyze real use but only the behavioral intention to use a technology. Recent studies such as by Agudo-Peregrina et al. (2014) show that the relationship between BI and actual use cannot always be confirmed or are of weak evidence and the prediction of behavior in health-related contexts varies (Godin and Kok 2016). Although Turner et al.'s (2010) review of 79 TAM-based studies concludes that BI is very likely to be correlated to the actual usage, this particular connection was not analyzed in this study and should be investigated in future research.

Despite these limitations, we believe that our exploratory empirical study is a valuable contribution to the acceptance research stream in general and the specific domain of self-tracking technology in particular. Last but not least, we suggest promising avenues for future research. First, it would be interesting to analyze if and how the relevant determinants change after the initial acceptance of a wearable self-tracking device (source blinded), considering the fact that determinants and their coefficients typically differ between the acceptance and the post-acceptance phase (Karahanna et al. 1999; Kim and Malhotra 2005). Second, while we focused on the three major types of self-tracking data, namely health, well-being and fitness, the role of other data types has been excluded from research. Also, we solely focused on perceived usefulness, perceived ease of use and perceived enjoyment as drivers for the intention to use wearable self-tracking devices. Thus, to gain a bigger picture about acceptance factors in the domain of self-tracking, further research should broaden the perspective, e.g. on the role of data privacy. For organizational practice, our results are useful to guide future product development.

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9. Appendix

Appendix A: Measurement Instrument

The measurement items for behavioral intention were adapted from Schlohmann (2012). The measurement items for perceived usefulness, perceived ease of use and perceived enjoyment were adapted from Venkatesh et al. (2003), Venkatesh et al. (2012), Lu et al. (2005) and Gefen et al. (2003). Regarding the remaining three determinants perceived support of well-being, perceived support of fitness, and perceived support of health, no suitable previous instruments could be identified. Thus, we developed own sets of items based on a review of recent literature on the use of self-tracking (Gimpel et al. 2013; Lupton 2013a, 2014b; Rooksby et al. 2014) as well as based on five interviews we conducted with users of self-tracking devices. Subsequently, our measurement instrument was subject to thorough pre-testing using card-sorting exercise.

Table 3: Operationalization

		Adapted from	Factor loading	Mean	SD
Behavioral Intention to Use Wearable Self-Tracking Devices					
BI1	With a high probability, I will use a self-tracking device in the future.	Schlohmann (2012)	0.950	3.70	1.78
BI2	If I get the opportunity, I will use a self-tracking device.	Schlohmann (2012)	0.891	4.52	1.72
BI3	I plan to buy a self-tracking device in the future.	Schlohmann (2012)	0.938	3.59	1.72
BI4	I will recommend others to also use a self-tracking device.	Schlohmann (2012)	0.900	3.50	1.61
Perceived Usefulness					
PU1	Overall, I find self-tracking devices useful in my daily life.	Lu et al. 2005	0.865	4.55	1.41
PU2	I can increase my self-discipline by using a self-tracking device.	Gefen et al. 2003	0.881	4.11	1.48
PU3	Self-tracking devices support me in reaching my goals.	Self-developed based on Lu et al. 2005 and Gefen et al. 2003	0.851	3.93	1.48
PU4	The usage of a self-tracking device may significantly increase my quality of life.	Lu et al. 2005	0.838	4.80	1.40

Perceived Ease of Use					
PEOU1	The handling of a self-tracking device is easy and simple for me to understand.	Venkatesh et al. 2003	0.913	5.35	1.12
PEOU2	The use of self-tracking devices does not have high requirements for the user.	Lu et al. 2005	0.828	5.16	1.15
PEOU3	Learning how to handle a self-tracking device is easy.	Gefen et al. 2003	0.911	5.35	1.11
PEOU4	The handling of self-tracking devices is uncomplicated.	Self-developed	0.899	5.18	1.11
Perceived Enjoyment					
PE1	Using self-tracking devices gives me fun.	Venkatesh et al. 2012	0.940	4.32	1.40
PE2	Using self-tracking devices gives me joy.	Venkatesh et al. 2012	0.928	4.26	1.40
PE3	It is fun to look at and analyze my collected data on the internet.	Self-developed	0.830	4.24	1.44
PE4	Self-tracking devices provide a high entertaining value.	Self-developed	0.884	4.80	1.54
Perceived Support of Fitness					
PSF1	Self-tracking devices motivate me to be more physically active.	Self-developed	0.884	4.94	1.40
PSF2	With a self-tracking device, I can better monitor my training activities.	Self-developed	0.837	5.46	1.16
PSF3	With a self-tracking device, I can tailor my nutrition better to my training activities.	Self-developed	0.770	4.50	1.40
PSF4	Due to the usage of a self-tracking device, I am physically more active.	Self-developed	0.901	4.63	1.38
Perceived Support of Health					
PSH1	The usage of a self-tracking device increases my health consciousness.	Self-developed	0.898	4.91	1.30
PSH2	Self-tracking devices make me take care of my body.	Self-developed	0.865	4.75	1.43
PSH3	Self-tracking devices can help me prevent diseases.	Self-developed	0.730	3.85	1.46
PSH4	The usage of a self-tracking device increases my sense of responsibility for my own body.	Self-developed	0.902	4.77	1.43
PSH5	The usage of a self-tracking device simplifies living healthier.	Self-developed	0.827	4.46	1.34

Perceived Support of Well-Being					
PWB1	Due to the usage of a self-tracking device, I do feel better.	Self-developed	0.936	4.02	1.36
PWB2	Due to the usage of a self-tracking device, my well-being increases.	Self-developed	0.948	4.06	1.37
PWB3	Due to the usage of a self-tracking device, I get the feeling to have control over my well-being.	Self-developed	0.903	4.26	1.55

Appendix B: Cross Loadings

Table 4: Cross Loadings

	BI	PU	PE	PEOU	PSF	PSW	PSH
BI1	0.950	0.677	0.548	0.107	0.526	0.657	0.561
BI2	0.891	0.699	0.626	0.140	0.556	0.632	0.590
BI3	0.938	0.647	0.524	0.083	0.491	0.633	0.541
BI4	0.900	0.678	0.553	0.122	0.536	0.669	0.605
PU1	0.573	0.865	0.550	0.143	0.645	0.621	0.601
PU2	0.704	0.881	0.677	0.105	0.612	0.684	0.580
PU3	0.675	0.851	0.547	0.050	0.602	0.722	0.649
PU4	0.562	0.838	0.532	0.118	0.674	0.627	0.650
PE1	0.579	0.622	0.940	0.178	0.499	0.611	0.501
PE2	0.589	0.637	0.928	0.171	0.525	0.610	0.521
PE3	0.465	0.527	0.830	0.140	0.403	0.483	0.403
PE4	0.557	0.620	0.884	0.197	0.500	0.574	0.485
PEOU1	0.132	0.127	0.166	0.913	0.175	0.125	0.179
PEOU2	0.118	0.114	0.152	0.828	0.181	0.116	0.139
PEOU3	0.114	0.106	0.198	0.911	0.151	0.081	0.132
PEOU4	0.067	0.069	0.164	0.899	0.134	0.057	0.122
PSF1	0.578	0.727	0.565	0.132	0.884	0.676	0.723
PSF2	0.410	0.563	0.413	0.185	0.837	0.475	0.622
PSF3	0.416	0.509	0.327	0.145	0.770	0.516	0.621
PSF4	0.566	0.696	0.522	0.115	0.901	0.669	0.706
PWB1	0.655	0.704	0.629	0.085	0.610	0.936	0.641
PWB2	0.683	0.742	0.593	0.103	0.653	0.948	0.696
PWB3	0.625	0.714	0.557	0.116	0.630	0.903	0.684
PSH1	0.570	0.680	0.489	0.108	0.727	0.662	0.898
PSH2	0.523	0.618	0.476	0.195	0.692	0.613	0.865
PSH3	0.470	0.477	0.363	0.085	0.509	0.519	0.730
PSH4	0.561	0.665	0.488	0.122	0.709	0.660	0.902
PSH5	0.521	0.592	0.437	0.174	0.693	0.603	0.827

Insights into the Usage Behavior of the Digitalized Individual: Understanding Continuance and Discontinuance of Wearable Self-Tracking Devices

Extended Abstract[1]

The use of wearable self-tracking devices such as wristbands and smartwatches became increasingly common during the last decade and the latest generation of these devices now also allow to run third-party applications and services on them. Yet, the associated business and service models of these third-party applications rely on the continuous supply with personal data recorded by the wearable self-tracking devices. Consequently, for the success of these applications and services, it is necessary that self-tracking device manufacturers and service-providers know what fosters the user's continuance intention and at the same time inhibits the formation of a discontinuance intention in order to secure regular and ongoing usage in the post-acceptance phase.

Previous studies have mostly focused on post-acceptance behavior with a focus on business technologies (Bhattacherjee et al. 2008; e.g. Bhattacherjee and Lin 2017; Furneaux and Wade 2011, 2017; Recker 2016) and business-consumer technologies (e.g. Bhattacherjee 2001; Chen et al. 2012; Cheung and Limayem 2005; Gong et al. 2018; Islam et al. 2017; Limayem et al. 2007; Limayem and Cheung 2008; Lin et al. 2014; Lin et al. 2017; Maier et al. 2015; Thong et al. 2006; Turel 2016; Vatanasombut et al. 2008; Venkatesh et al. 2011; Zhou 2013; Zhou et al. 2018) and thus in a context of a weak to medium personal connection of the corresponding technology with the user. In contrast, little research has been carried out to date in the context of post-acceptance behavior for technologies that have a strong personal connection with the user by processing highly personal and often confidential data and initiating changes, emotions, and new habits. The goal of this research paper therefore is to analyze factors that lead to continuance and discontinuance within the unique context of wearable self-tracking devices.

To do so, we develop a conceptual model based on established post-acceptance concepts and the dual-factor approach with a set of 12 hypotheses and empirically evaluate it using survey data collected from 357 active self-tracking users by applying structural equation modeling.

[1]At the time of publication of this thesis, this paper is in the review process of a scientific journal. Thus, I provide an extended abstract that covers the paper's content.

Our results reveal the simultaneous influence of continuance and discontinuance intentions on wearable self-tracking use as well as a significant effects of perceived usefulness and affective-based inertia on the continuance intention. In addition, system unreliability, perceived routine constraints, trust and negative social influence drives the discontinuance intention. In contrast, no significant influence was found for perceived cognitive based inertia, sunk costs and positive social influence on the continuance intention and for system capability shortcomings on the discontinuance intention.

Conclusively, whereas previous research primarily focused on post-acceptance behavior of technology that has a less intense connection and only explained continuance or discontinue behavior separately, we extend the research stream by focusing on self-tracking devices as an example of a technology with a strong personal connection with the user and by employing a dual-factor approach. Our major theoretical contributions are twofold: First, we show that domain-specific factors are particularly important whether or not a self-tracking user continues or discontinues using a device. Second, we show that both enabling and inhibiting factors influence simultaneously the use behavior of the self-tracking device user. Additionally, we provide practical implications for the design of the hardware, software and the associated ecosystem of wearable self-tracking devices, by showing that functionalities should be usefulness and enjoyability, while they also should interact seamlessly with the user to minimize the disturbance of daily routines as much as possible.

Keywords: Self-tracking, digitalization of the individual, information systems (dis)continuance, technology post-acceptance, technology use, user behavior

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The New Age of Data-Driven Services – Investigating Drivers and Inhibitors of the Willingness to Disclose Personal Self-Tracking Data

Extended Abstract[1]

Users of digital self-tracking devices increasingly benefit from multiple data-driven services related to their self-tracking data. Vice versa, new digital as well as traditionally "offline" service providers, such as health insurance companies or physicians, depend on the users' willingness to disclose highly personal self-tracking data to be able to offer new data-driven services. Whereas previous research mostly investigated the willingness to disclose personal data in the context of social media, e-commerce, smartphone apps, location-based services and health, the research base for highly personal data disclosure and privacy within the context of self-tracking is still limited (e.g. Becker et al. 2017; Becker 2018; Seifert et al. 2018; Wieneke et al. 2016; Zhang et al. 2015). We therefore aim to extend the research base by analyzing the influence of the privacy calculus of personal risks and benefits on the willingness of a user to disclose highly personal self-tracking

To do so, we develop and empirically validate a research model that is based on the comprehensive APCO Macro Model (Antecedents, Privacy Concerns, Outcomes) of Smith et al. (2011) and focus on the link between the privacy calculus and the behavioral reactions. We contribute to the specific context of self-tracking by considering the two contextual factors data sensitivity (Li et al. 2016) and sharing preference (Caine and Hanania 2013).

Concerning the data sensitivity, we distinguish between activity data as a proxy for weak data sensitivity and health data for strong data sensitivity (Becker et al. 2017). In terms of the sharing preference, we focus solely on traditionally "offline" service providers since they provide an interesting near-future scenario (Bucher 2017; My Doctor Medical Group 2019) but are underrepresented in research. In detail, health insurance companies as a proxy for a low sharing preference and family physicians for a high sharing preference are considered (Caine and Han-

[1]At the time of publication of this thesis, this paper is in the review process of a scientific journal. Thus, I provide an extended abstract that covers the paper's content.

ania 2013). In addition to the contextual factors, the perceived activity condition and the perceived health condition of the self-tracking device users is also taken into consideration by implementing these factors as moderators into the research model (Bansal et al. 2010; Tisnado et al. 2006). This allows to create four groups and compare the results regarding weak (activity) and strong (health) data sensitivity as well as low (health insurance company) and high (family physician) sharing preference.

The analysis results based on an online survey with 286 responses and structural equation modeling reveal, that both privacy risks and service improvement benefits positively as well as financial rewards negatively influence the user's willingness to disclose highly personal self-tracking data in each of the analyzed groups.

Yet, a moderating effect is present on the relationship of privacy risks and the willingness to disclose personal self-tracking data within the two groups of high sharing preference (family physician). In detail, a high concern of privacy risks has a significantly lower negative effect on the willingness to disclose personal self-tracking data for users with a high perceived activity or health condition. While there is no such moderating effect within the two groups of low sharing preference, it is an indicator that health insurance companies are seen as more critical than family physicians.

Another moderating effect is present within the group of low sharing preference and weak data sensitivity. Here, a high appreciation of service improvement benefits has a significantly higher positive effect on the willingness to disclose personal self-tracking data for users with a high perceived activity condition. However, since the moderator effect only appears in one of the four groups, the lack of clear analysis patterns in this regard calls for further in-depth research.

Conclusively, while the research paper is among the first to advance the theoretical understanding in this new and unique context, it also provides practical service design implications for practitioners. It is shown, that service improvement benefits and financial rewards benefits based on self-tracking data could be used to increase convenience and quality of services and to foster desired positive behaviors, respectively. In contrast, privacy concerns have to be taken seriously, for example by high transparency about the data usage or an external certification of the privacy standards.

Keywords: Digital Self-Tracking Devices, Privacy Calculus, Data Disclosure, Privacy, Data-Driven Services, Service Provider

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Self-Tracking and Gamification: Analyzing the Interplay of Motivations, Usage and Motivation Fulfillment

Abstract

The usage of wearable self-tracking devices has emerged as a big trend in lifestyle and personal optimization concerning health, fitness, and well-being. In this context, gamification elements have the potential to contribute to achieving desired user behavior. However, it is not fully understood to which extent the users perceive their self-tracking motivations as being fulfilled through the usage of a wearable self-tracking device, and how gamification affects the interplay of self-tracking motivations, wearable self-tracking device usage, and motivation fulfillment. To address this research gap, we develop a conceptual model and validate it with survey research and structural equation modeling. We find that self-tracking helps users to unexpectedly fulfill motivations without previously striving for them and that significant differences exist between the gamification users and non-users with respect to their motivations by self-entertainment and self-design.

Keywords: Self-tracking, Gamification, Wearable Self-tracking Devices, Motivation Fulfillment, Five Factor Framework of Self-tracking Motivations

Table of contents – Essay 4

1. Introduction

The engagement in self-tracking has recently emerged as a big trend in personal optimization and lifestyle (Pfeiffer et al. 2016). Self-trackers regularly gather data about themselves – often related to their bodily functions and everyday habits – and then analyze the data to produce statistics and other analyses, such as images and diagrams (Choe et al. 2014), (Sjöklint et al. 2015). Devices used for this practice include for example smartphones, tablet computers, and so-called wearables. These wearable self-tracking devices benefit from sensors getting smaller as well as more compactly integrated (Choe et al. 2014). Wearable self-tracking devices are, for example, smartwatches, wristbands, patches, clip-on devices, and jewelry or textiles with embedded sensors which measure bodily functions or physical activity (Swan 2012). The hype about self-tracking is also driven by the fact that "the new possibilities through technology have opened up a world that offers new ways to get to know oneself and to gain a profound, fact-based understanding of collected self-related data" (Gimpel H. et al. 2013, p. 13).

In this regard, research on self-tracking has also emerged as a distinct stream within the IS community in recent years, studying various facets of the phenomenon (Sjöklint et al. 2015), (Baumgart and Wiewiorra 2016; Buchwald et al. 2015; Lupton 2014). One of these facets is dedicated to understand the role of the user's motivations to engage in the practice of self-tracking. Therefore, Gimpel et al. developed a five factor framework of self-trackers' deep underlying motivations (Gimpel H. et al. 2013), while Baumgart and Wiewiorra (Baumgart and Wiewiorra 2016) analyzed what motivations to start self-tracking drive different self-tracking activities and how different levels of self-control influence the tracking behavior of consumers and their expenditures. However, from an end-to-end perspective, a still unanswered question is to which extent the user's initial motivations are actually fulfilled through the practice of self-tracking. We therefore aim to advance this research path by investigating to which extent the users actually perceive the motivations to self-track as being fulfilled by using their wearable self-tracking devices:

RQ1: How does the usage of wearable self-tracking devices influence the user's perceived fulfillment of the initial motivations?

In the context of self-tracking motivation and motivation fulfillment, the practice of gamification should be considered. Gamification is a powerful method for motivating and influencing people (Bunchball Inc. 2010). Its term arose from the digital media industry (Deterding et al. 2011) and describes the idea of using game design elements in non-game contexts (Deterding et al. 2011). One might think that gamification relates to only the motivational factor self-entertainment – below we do however argue theoretically and show empirically that gamification also significantly relates to other motivational factors. Within self-tracking experience, the application of gamified elements has the potential to change the user's behavior (Lister et al. 2014). For example, gamification elements such as rewards, levels, leaderboards, goal-setting, and feedbacks (Lister et al. 2014), (Zuckerman and Gal-Oz 2014) are attributed to facilitate the attractiveness of monotonous physical activities (Rapp et al. 2012) and therefore motivate users to become more active (Zuckerman and Gal-Oz 2014). Consequently, when investigating self-tracking motivations and motivation fulfillments, the concept of gamification should be considered as it can be expected to influence the relationships between Gimpel et. al's (Gimpel H. et al. 2013) self-tracking motivations, actual wearable self-tracking device usage, and fulfillment of the initial motivations. Therefore, we also strive to answer the following research question:

RQ2: How does the usage of gamification elements within the wearable self-tracking device influence the interplay of self-tracking motivations, wearable self-tracking device usage, and motivation fulfillment?

To answer our two research questions, we develop and test a conceptual model based on the research models of Gimpel et al. (Gimpel H. et al. 2013) as well as Baumgart and Wiewiorra (Baumgart and Wiewiorra 2016). Further, we investigate the influence of the motivational factors of the five factor framework on the self-tracking usage and ultimately the influence of usage on the motivation fulfillment. Finally, we integrate gamification usage as a moderator to test the effect on the interplay of self-tracking motivations, wearable self-tracking device usage, and motivation fulfillment.

2. Foundations

2.1. Wearable self-tracking device usage and motivations

Wearable self-tracking devices can be assigned to the category of personal information and communication technology (ICT) devices since they are mobile (used on, e.g., the user's wrist), are adopted by individuals for their own personal usage, and enable users to engage in various activities with one device (Hong and Tam 2006), (Scheepers and Middleton 2013). To understand the users adoption of these devices, device-specific research was conducted for smartwatches (Kim and Shin 2015), (Chuah et al. 2016) and for fitness-trackers (Sol and Baras 2016).

Further, on a more comprehensive level, Pfeiffer et al. examined what factors drive the user's pre-adoption of wearable self-tracking devices, showing perceived usefulness, perceived enjoyment, social influence, trust, personal innovativeness, and perceived support of well-being to be the major drivers for the intention to use wearable self-tracking technologies (Pfeiffer et al. 2016). In addition, Buchwald et. al. extended research in this area by developing a model explaining post-adoption of self-tracking devices and showed that self-tracking device usage is influenced by continuance as well as discontinuance factors (Buchwald et al. 2018).

In contrast to these adoption models which focus on the user's perceptions about the characteristics of the self-tracking technology and its usage, Gimpel et al. developed a five-factor framework of self-tracking motivations. This comprehensive study identifies and characterizes the deeper underlying motivations of users to engage in the practice of self-tracking (Gimpel H. et al. 2013). Those five motivations are:

Self-entertainment: Being motivated by the fun and ludic aspects of self-tracking. Key drivers are the enjoyments of getting lost totally in self-tracking activities, forgetting about time while doing so or playing around with numbers, statistics etc.

Self-association: Being motivated by self-individualizing aspects within a community as well as the prospect of community membership. Respective reasons causing self-tracking activities are such as the urge of comparing own results to others, helping or inspiring others, and presenting oneself to them.

Self-design: Being motivated by the chances of self-optimization such as the desire to control, optimize or even manipulate certain aspects of one's life or the enjoyment of being one's own master.

Self-discipline: Being motivated by the self-gratification possibilities of self-tracking. Decisive aspects are the facilitation of one's self-discipline, the motivation to keep on working for a goal and the chance to reward oneself.

Self-healing: Being motivated by the possibilities of self-tracking to take care of one's own health. Major factors are the aspiration of being independent from traditional medical treatments and the distrust in the healthcare system as well as classical therapies.

Gimpel et al.'s results show on the one hand that more self-tracking motivation on any of the single factors enhances the number parameters tracked as well as the time spent on self-tracking. These two constructs are defined by Gimpel et al. as self-tracking activity. On the other hand, motivation from every factor is rather independent from demographic factors (age, gender) and of personality traits (e.g. openness, conscientiousness or extraversion). Baumgart and Wiewiorra (Baumgart and Wiewiorra 2016) further analyzed how different levels of self-control influence the tracking behavior of consumers and their expenditures for self-tracking software and hardware as well as what motivations to start self-tracking drive different self-tracking activities. They found out that the motivation of increasing one's performance as well as the number of tracked physical parameters are the key drivers of self-tracking usage frequency and accumulated expenditures. Further, customers that started self-tracking out of pure curiosity spend significantly more on self-tracking software, services and hardware and are at the same time more likely to track parameters from a wider variety of categories. Finally, they also showed that higher levels of self-control increase the odds of consumers tracking physical parameters and spending more on self-tracking software and hardware.

2.2. Gamification in the context of self-tracking

Gamification is the use of game design elements in non-game contexts (Deterding et al. 2011) for changing people's behavior and driving participation as well as engagement (Bunchball Inc. 2010). Gamification, often interchangeably called "gamified services" (Hamari and Huotari 2012), "gamefulness", or "gameful design" (Stieglitz et al. 2017), also aims at the enhancement of positive patterns in service use like increasing quality and productivity of user actions, social interactions, or user activity (Hamari et al. 2014).

Gamification can be reached by integrating game mechanics or elements and game dynamics. These terms are closely related and sometimes used synonymously (Bunchball Inc. 2010). Game elements are composed of multiple facets of "game play" (Burke and Hiltbrand 2011) in the form of various actions, behaviors, and control mechanisms. While literature offers a wide range of different gamification elements (Zuckerman and Gal-Oz 2014), (Burke and Hiltbrand 2011; Thiebes S. et al. 2014; Zichermann and Cunningham 2011), rewards, levels, leaderboards, goal-setting, and feedbacks are specific gamification elements particularly considered in the context of self-tracking (Lister et al. 2014), (Zuckerman and Gal-Oz 2014). They are the means which are used to create a compelling and appealing user experience (Bunchball Inc. 2010) and ensure the user's engagement and his continuance in system usage (Burke and Hiltbrand 2011). Thereby, game dynamics, e.g., status, altruism, or achievement, are defined as the desires and motivations triggered by game elements. They are the universal human needs across genders, cultures, demographics, and generations which appropriate sets of game mechanics aim to satisfy (Bunchball Inc. 2010). Overall, gamification elements can be seen as the means which are used to satisfy game dynamics and thus, ultimately, fulfill the inherent underlying self-tracking motivations.

As mentioned before, self-trackers strive for optimizing certain aspects of their lives (Gimpel H. et al. 2013). Especially with challenging and difficult behavior patterns for such self-optimization, users' motivation needs to be maintained in the long run. This is where gamified self-tracking applications which are designed to change the users' behavior (Lister et al. 2014), (Hamari and Koivisto 2015) come into play. One possible underlying intention could be to motivate them to become more active by making physical activity more enjoyable (Zuckerman and Gal-Oz 2014). For example, monotonous physical activities such as running workouts can gain attractiveness by more intensively integrating the user into the application (Rapp et al. 2012). Gamification is also able to contribute positively to the usage of self-tracking apps as long-term goals can be broken down into sub-goals that can be attained more quickly. The gamification element challenges, for example, allows the user to repeatedly achieve short-term targets set by the application and might reward the user afterwards. A user planning to lose 20 kg by running might feel discouraged at first due to the long way to go. But as the application motivates the user to do single and short workouts step-by-step, the sub-goals are easier to realize. This supports the user's motivation to continuously strive for his goals (Wellmann and Bittner 2016).

Next to positive impacts of gamification on motivation in the context of self-tracking applications, also negative aspects have been identified. According to the self-determination theory of human motivation (Deci and Ryan 1996), competence, relatedness, and autonomy are the three innate psychological needs that determine motivation. On the one hand, intrinsic motivation gets enhanced when these needs are satisfied, but on the other hand, they diminish intrinsic motivation when they are thwarted (Zuckerman and Gal-Oz 2014). Generally, game-play is voluntary as well as free of consequences and hence facilitates perceived autonomy, which is intrinsically motivating. But when it comes to gamified systems offering rewards or social comparison (e.g., leaderboards), their use is not necessarily voluntary or free of consequence. This might thwart perceived autonomy and hence intrinsic motivation (Deterding 2011). Taken to a more general level, Nicholson (Nicholson 2012) claims that by artificially integrating gamification elements into non-game activities, motivation will be reduced in the long run.

Besides the influence of gamification on motivations, Wellmann and Bittner (Wellmann and Bittner 2016) as well as Gal-Oz and Zuckerman (Zuckerman and Gal-Oz 2014), expanded the research stream by investigating the influence of gamification on the user's absolute, measurable goal achievement. They examined whether a gamified version of a smartphone app can affect self-tracker's physical activity. Wellmann and Bittner discovered that gamification elements within a running app can increase the user's movement behavior as their running distance was significantly larger (Wellmann and Bittner 2016). In contrast, Gal-Oz and Zuckerman concluded that their gamified application which measures walking is only as effective as the version excluding gamification elements (Zuckerman and Gal-Oz 2014).

3. Conceptual Development

3.1. Motivations and usage

IS usage can be described as the "degree and manner in which an IS is utilized by its users" (Urbach and Müller 2011, p. 6). While perceptions of characteristics of an information system (e.g. perceived ease of use or usefulness) in general and self-tracking-specific influencing factors of usage have been extensively studied before (e.g., (Pfeiffer et al. 2016), (Buchwald et al. 2018), (Buchwald et al. 2017; Davis 1985; Venkatesh et al. 2003; Venkatesh et al. 2012)), we deliberately focus on the user's underlying motivations and assume that those influence the usage behavior of a wearable self-tracking device as well. For example, the desire for self-design concerning sleep-optimization can be fulfilled by an ongoing monitoring of sleeping patterns with a sleep-tracker, thus inducing its usage. Therefore, we adapt the previously described five motivational factors identified by Gimpel et al. (Gimpel H. et al. 2013) and hypothesize:

The motivations for self-entertainment (H1.1), self-association (H1.2), self-design (H1.3), self-discipline (H1.4), and self-healing (H1.5) have a positive effect on the usage of wearable self-tracking devices.

3.2. Motivation fulfillment

After the initiation of wearable self-tracking device usage through self-tracking motivations, we assume that the continuous usage of a wearable self-tracking device leads to the perceived fulfillment of the initial motivations. For example, the initial motivation for self-discipline causes an ongoing usage of a device in terms of setting and controlling testable goals like the number of steps walked or calories burned. With the ongoing feedback of the device on these measures, the user feels his need for self-discipline being fulfilled by the device. In this regard, we define motivation fulfillment as the perceived fulfillment of the intrinsic desires reflected in the manifestation of a motivation. We further stay with five factor framework of self-tracking motivations (Gimpel H. et al. 2013), but now do consider the motivations fulfillment and hypothesize:

Wearable self-tracking device usage positively affects the user's motivation fulfillment of self-entertainment (H2.1), self-association (H2.2), self-design (H2.3), self-discipline (H2.4), and self-healing (H2.5).

3.3. Moderating effect of gamification usage

Gamification has often shown to have positive effects on motivation (Bunchball Inc. 2010), (Lister et al. 2014; Rapp et al. 2012; Zuckerman and Gal-Oz 2014), (Wellmann and Bittner 2016) and distinct goal achievement (Wellmann and Bittner 2016) in the context of self-tracking. A literature analysis as well as a self-conducted analysis of the top 20 iOS applications within the category of health and fitness has shown that levels, rewards, challenges, and leaderboards can be considered as the most relevant gamification elements (Lister et al. 2014), (Zuckerman and Gal-Oz 2014). To adapt this characteristic of gamification to the context of self-tracking, we conjecture a moderating impact of gamification usage, which influences the effect of motivations for self-tracking on the actual wearable self-tracking device usage. Consequently, we suppose the positive effects of gamification on motivation to be predominant and posit:

Gamification usage positively moderates the effect of the motivations self-entertainment (H3.1.1), self-association (H3.1.2), self-design (H3.1.3), self-discipline (H3.1.4), and self-healing (H3.1.5) on wearable self-tracking device usage.

As gamification can also, in general, enhance system usage (Rapp et al. 2012), we adapt this characteristic of gamification to the self-tracking context. We assume that the user's continuous usage of wearable self-tracking devices leads to a satisfaction of her or his motivations and therefore hypothesize gamification usage to also moderate the effect of wearable self-tracking device usage on motivation fulfillment. Again, we suppose the positive effects of gamification on motivation fulfillment to be predominant and hypothesize:

Gamification usage positively moderates the effect of wearable self-tracking device usage on the motivation fulfillment of self-entertainment (H3.2.1), self-association (H3.2.2), self-design (H3.2.3), self-discipline (H3.2.4), and self-healing (H3.2.5).

3.4. Research model

Summarizing, the final research model including all moderating effects consist of twenty hypotheses and is summarized in Figure 1.

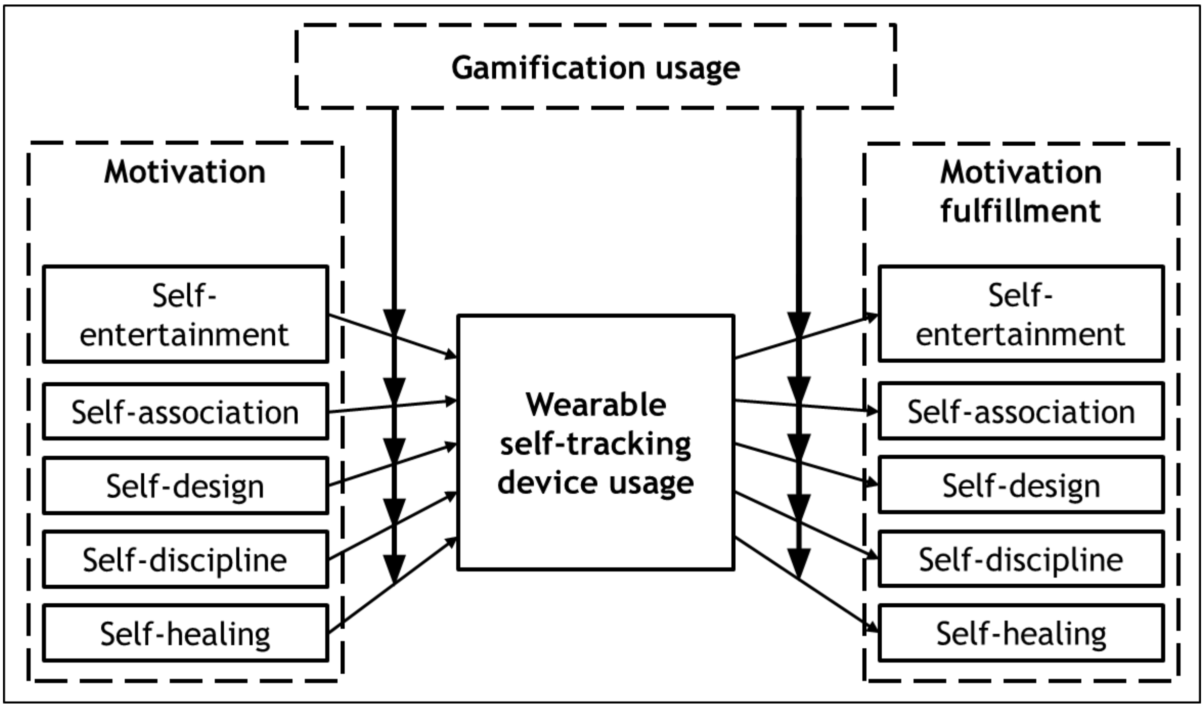

Figure 1: Proposed Conceptual Model

4. Survey design and procedures

We chose a quantitative-empirical research approach to validate our conceptual research model because it allows for a statistical generalization on the basis of results which are representative of the whole population at a lower cost than collecting the data for the whole population (Saunders et al. 2009, p. 144). To this end, we crafted a survey instrument. We began this process by using, wherever possible, established and validated measurement scales and adapted them if necessary, to ensure that the focus of our study is centrally reflected in each of the statements. Each of the item statements was measured with a seven-point Likert scale (Likert 1932). All constructs are measured reflectively.

To further enhance the survey instrument's comprehensibility and validity, we conducted a pretest with six researchers and incorporated their qualitative feedback. Ultimately, we used our survey instrument to collect empirical data via an online-survey tool.

4.1. Construct operationalization

We measure both self-tracking motivation (M-) and motivation fulfillment (F-) based on the five factors self-entertainment (SE), self-association (SA), self-design (SDe), self-discipline (SDi), and self-healing (SH) (Gimpel H. et al. 2013). We utilize all items from (Gimpel H. et al. 2013) to measure both the current self-tracking motivation and motivation fulfillment. For the measurement of current self-tracking motivation, the items represent answers to the originally proposed question "I am self-tracking because…" (Table 1 lists all items) and range from "strongly disagree" to "strongly agree". For each item, this question regarding self-tracking motivation was immediately followed by an evaluation of the phrase "I actually fulfill this goal by self-tracking." to capture motivation fulfillment. The answer-options range from "not fulfilled as I expected" to "fulfilled way more than I expected". In addition, we added the scale item "not applicable as not a goal of mine" in the motivation fulfillment.

Table 1: Operationalization of self-tracking motivation (Gimpel H. et al. 2013)

Constructs	**Items** **I am self-tracking because…**
Self-entertainment (SE)	... I enjoy getting lost totally in self-tracking activities.
	... I like playing around with numbers/statistics etc.
	... I like playing around with my smartphone/technical device etc.
	... I enjoy forgetting about time while doing so.
	... it is fun and entertaining.
Self-association (SA)	... I want to help/inspire others.
	... the way I'm doing it is interesting for others/might help others.
	... I want to compare my results to others.
	... I want to present myself to others.
Self-design (SDe)	... I want to control what I'm doing with my life.
	... I try to manipulate certain aspects in my life.
	... I enjoy being my own master.
	... I'm interested in how certain things in (my) life interact.
	... it helps me to optimize the way I'm living.
Self-discipline (SDi)	... it motivates me to keep on working for a goal.
	... It allows me to reward myself.
	... it facilitates my self-discipline.
Self-healing (SH)	... I don't trust in the healthcare system/classic therapies.
	... I want to be independent from traditional medical treatments.

Further, we self-developed two measurement items for wearable self-tracking device usage (WSTDU) based on Burton-Jones and Straub (Burton-Jones and Straub 2006), Davis et. al (Davis et al. 1989) as well as Venkatesh and Davis (Venkatesh and Davis 2000). The answer-options range from “Less than few times a month” to “Almost 24 hours a day”. Regarding gamification usage, we differentiate between active self-tracking users if they at least use one of the four considered gamification elements rewards, levels, leaderboards, and challenges and those who do not engage with any of these elements. Thus, gamification usage represents a binary variable. The final operationalization of wearable self-tracking device usage (WSTDU) and gamification usage is shown in Table 2.

Table 2: Operationalization of wearable self-tracking device usage (WSTDU)

Constructs	Items
WSTDU	On average, how frequently do you (passively) collect data with your wearable self-tracking device?
	On average, how frequently do you actively engage with your wearable self-tracking device (e.g., for data analysis)?
Gamification usage	Do you use the gamification element *Rewards / Levels / Leaderboards / Challenges* within your wearable self-tracking device? [Four items, one each for the four gamification elements]

4.2. Data collection

We collected data by administering our survey instrument to current active users of wearable self-tracking devices. This means that it was a prerequisite that the users actively use their device to track their fitness, health, or well-being to increase the validity of the responses. Users who do not yet use or have already stopped using their devices were excluded from the survey. We explained to the participants the concept of self-tracking and the function of the different gamification elements to receive more valid responses. To gather our data, we offered English and German versions and distributed the invitation message to participate in our study in online social networks (e.g., Facebook), online business networks (e.g., Xing and LinkedIn), instant-messaging services (e.g., WhatsApp), and the e-learning system of one of the authors' universities. We decided to openly circulate our invitation to allow for a snowball effect within social media. Overall, we received 359 responses. We excluded non-self-tracking users and incomplete answers (270 in total) which left us with 89 remaining responses. Of these 89 respondents, 53% indicated that they are actively using at least one of the four gamification elements. The average time of usage for the wearable self-tracking devices was 20 months. 84% use smartphone apps for self-tracking, 33% an activity tracker, 17% a smartwatch and 10% another form of device or application. On a seven-point Likert scale ranging from light user (1) to heavy user (7), 52% of the sample group consider themselves as medium self-tracking user type (4) or higher. On a seven-point Likert scale ranging from strongly disagree (1) to strongly agree (7), 64% either agree (6) or strongly agree (7) to be interested in trying out new technical devices. 57% agree or strongly agree that they actively take care of their health and well-being and 51% that they see themselves as sportive.

5. Data analysis and results

We tested measurement properties and hypotheses with a partial least squares structural equation modeling approach (PLS-SEM) and multi-group analysis (MGA) (Wold 2005), (Chin 1998) using the software SmartPLS Version 3.2.6 (Ringle et al. 2015). Even though PLS-SEM has its limitations (Tomarken and Waller 2005), we chose it as an established approach in the IS research discipline and for our study especially due to the relatively small sample size (Gefen et al. 2011), (Hair et al. 2017).

5.1. Measurement model

Concerning outer loadings, we set the critical threshold at 0.70 (Hair op. 2017). The outer loadings of the fourth item of self-entertainment motivation and motivation fulfillment, the second item of self-discipline motivation and motivation fulfillment, and the third item of self-design motivation and motivation fulfillment are lower than 0.70. We excluded them from our measurement model. The first two items of self-association motivation and the last two items of self-association motivation fulfillment exhibit lower outer loadings than 0.70 as well. Due to the nature of our measurement model, dropping these items would lead to an asymmetric inconsistency between the constructs. We therefore further examined the data and the operationalization of the construct. The results suggest that the operationalization may describe two different facets of self-association, one more directed towards altruism, the other more towards self-presentation. Hence, we decided to not further consider the results of self-association. Furthermore, the first item of self-entertainment motivation and the first and fifth item of self-entertainment motivation fulfillment do not reach the critical threshold of 0.70. But as they still exceed 0.60, which is deemed high (Gefen et al. 2003), we considered them as marginal and did not exclude them from our measurement model. All other items, including active as well as passive use frequency of the construct wearable self-tracking device usage are greater than the critical threshold. Adhering to standard validation guidelines (Lewis et al. 2005; Straub et al. 2004; Urbach and Ahlemann 2010), we tested the reflective measurement model in terms of internal consistency reliability, indicator reliability, convergent validity, and discriminant validity. The internal consistency reliabilities (composite reliability) of multi-item scales modeled with reflective indicators is 0.81 or greater, suggesting that scales were reliable. In addition, the Cronbach's Alpha values are, except for self-association, 0.70 or greater, hence showing a good internal consistency of our scale. The average variance extracted is consistently greater than the critical threshold of 0.50. Hence, we conclude that convergent validity has been established.

The complete results are presented in Table 3.

Table 3: Measurement Model's Results

Latent Variable	CA	CR	AVE
Motivation for Self-Design (M-SDe)	0.781	0.855	0.596
Motivation for Self-Discipline (M-SDi)	0.822	0.894	0.810
Motivation for Self-Entertainment (M-SE)	0.702	0.815	0.525
Motivation for Self-Healing (M-SH)	0.886	0.910	0.836
Wearable self-tracking device usage (WSTDU)	0.797	0.908	0.831
Self-Design motivation fulfillment (F-SDe)	0.776	0.855	0.596
Self-Discipline motivation fulfillment (F-SDi)	0.833	0.916	0.846
Self-Entertainment motivation fulfillment (F-SE)	0.741	0.831	0.553
Self-Healing motivation fulfillment (F-SH)	0.907	0.953	0.910
Notes: CR = Composite Reliability, AVE = Average Variance Extracted, CA = Cronbach's Alpha			

Further, to check for discriminant validity, we applied the Fornell-Larcker Criterion as a conservative measure (Fornell and Larcker 1981). The square root of each construct's AVE is greater than its highest correlation with any other construct, hence discriminant validity has been established, too. The results are presented in Table 4. In addition, we checked the cross loadings and all items have the highest loadings with the construct with which they are theoretically related (Appendix Table 6)

Table 4: Correlations and Square Roots of AVE Values

	M-SDe	M-SDi	M-SE	M-SH	F-SDe	F-SDi	F-SE	F-SH	WSTDU
M-SDe	0.772								
M-SDi	0.563	0.900							
M-SE	0.196	0.040	0.725						
M-SH	0.356	0.012	0.189	0.914					
F-SDe	0.731	0.335	0.205	0.170	0.772				
F-SDi	0.415	0.664	0.117	-0.013	0.584	0.920			
F-SE	0.166	0.055	0.724	0.132	0.395	0.271	0.744		
F-SH	0.267	-0.088	0.262	0.464	0.450	0.169	0.488	0.954	
WSTDU	0.287	0.235	0.304	0.047	0.326	0.321	0.242	0.139	0.912

5.2. Structural model

To assess the significance levels of our structural model including the MGA, we applied bootstrapping with 5,000 sub-samples (no sign changes). Table 5 presents the results for the entire group and for the sub-groups of gamification users and non-users. Relating to the 20 hypotheses posed, 4 could not be tested due to measurement problems with self-association. Of the remaining 16 hypotheses, 7 are supported by the data. These seven hypotheses are discussed in the following. In that, we apply a 10% significance level which appears reasonable given the relatively small sample size, especially in the subgroups. Our data support that the motivation for self-entertainment increases the wearable self-tracking device usage and the latter positively influences the user's self-entertainment motivation fulfillment (H1.1 and H2.1). Further, the multi-group analysis of gamification users and non-users shows a significant difference between the two groups, with a significantly higher effect of motivation for self-entertainment on usage within the group of gamification users (H3.1.1).

Table 5: PLS-MGA Results

Hypothesis	Complete		Non-gamification users	Gamification users	Group delta
	n = 89		n = 42	n = 47	
	Path coefficients	R^2	Path coefficients		
M-SE → WSTDU	0.276 **	0.163	0.092	0.428 **	0.337 +
M-SDe → WSTDU	0.195		0.423 +	0.041	0.382 +
M-SDi → WSTDU	0.115		0.027 +	0.137	0.110
M-SH → WSTDU	-0.076		-0.248	0.044	0.292 +
WSTDU → F-SE	0.242 *	0.058	0.238	0.297	0.059
WSTDU → F-SDe	0.326 ***	0.106	0.491 ***	0.235	0.256
WSTDU → F-SDi	0.321 ***	0.103	0.434 ***	0.218	0.215 +
WSTDU → F-SH	0.139	0.019	0.244 *	0.168	0.076
Significance levels: + 10%, * 5%, ** 1% *** 0.1% | n = number of cases					

Self-design shows significant results as well: Wearable self-tracking device usage significantly increases the user's self-design motivation fulfillment (H2.3). Additionally, within the multi-group analysis, the influence of motivation for self-design on usage is significantly higher in the group of non-gamification users (H3.1.3). Also, our results reveal that wearable self-tracking device usage significantly increases the self-discipline motivation fulfillment (H2.4). Finally, the multi-group analysis results show that the influence of wearable self-tracking device usage on the self-discipline motivation fulfillment is significantly higher in the non-gamification group (H3.2.4).

6. Discussion

Taking a comprehensive look at our results, we acknowledge the relatively low R^2 values of the dependent variables. However, the results are reasonable since our study specifically only aims on the user's deeper underlying motivations of self-tracking and does not take the user's perceptions about the characteristics of the self-tracking technology and its usage into account which were analyzed in other dedicated acceptance studies (Pfeiffer et al. 2016), (Buchwald et al. 2018). Looking further into the details of our results, self-entertainment is the key motivation to engage in the practice of self-tracking as it is the only effect on wearable self-tracking device usage that is significant. Users seem to be driven by the entertainment possibilities which allow them to experience fun and play around with their collected data and statistics. Concerning the multi-group analysis, the effect is even more pronounced among gamification users and significantly differs from that of non-gamification users. This observation confirms that the playful elements of gamification reinforce the urge to self-track due to ludic motivation.

In contrast, the motivations self-design, self-discipline and self-healing are not found to drive wearable self-tracking device usage per se. However, the MGA shows that the motivation for self-design has a significantly higher influence on usage for non-gamification users. A potential reason could be, that non-gamification users who pursue control and optimization engage in these activities with a more serious mindset, thus deliberately ignore playful gamification elements because they might not support or even distract them.

Moving on to the relationships between wearable self-tracking device usage and motivation fulfillment, results show that usage significantly increases the perception that the preexisting desire for self-entertainment is fulfilled. The users of wearable self-tracking devices feel that their wishes to entertain themselves are met in the process of self-tracking. For self-design and self-discipline, however, we observe significant positive effects of usage on perceived motivation fulfillment without significant preexisting connections between their motivation and usage. Hence, users might not necessarily start self-tracking due to a striving for self-design or self-discipline. Nevertheless, as soon as they are active wearable self-tracking device users, they seem to realize positive effects such as being able to take control of and optimize their lives, gaining knowledge about interactions of certain things within their lives (self-design), facilitating their self-discipline, or being motivated to keep on working on goals (self-discipline). A further look at the group of non-gamification users reveals that they clearly and highly significantly perceive their motivation for self-discipline as better fulfilled than gamification users. This fact seems counterintuitive; however, a possible explanation here might also be that gamification elements do not support motivation fulfillment but rather distract the users from it.

7. Conclusion

The purpose of this study was to create a basis for future research regarding the analysis of the interplay of self-tracking motivations, usage and motivation fulfillment. Therefore, our paper investigates how Gimpel et. al's (2013) motivational factors for self-tracking influence the actual usage of wearable self-tracking devices, to which extent the users actually perceive these motivations as being fulfilled in the process of using them, and how gamification affects this interplay of self-tracking motivations, wearable self-tracking device usage, and motivation fulfillment. We found the motivation for self-entertainment to represent the crucial driver of wearable self-tracking device usage and ultimately usage as important driver for the motivation fulfillment of the three factors self-entertainment, self-discipline, and self-design. Further, both the motivation as well as the motivation fulfillment are moderated by gamification usage. Gamification users are more motivated by self-entertainment, non-gamification users more by self-design. In addition, non-gamification users tend to have higher levels of motivation fulfillment, except for self-entertainment. Hence, in designing self-tracking devices and apps and potentially integrating gamification elements, one should carefully consider the diverse effects of gamification.

Our study has three main limitations: First, as common in research on motivation, survey responses are self-reports. Second, our results are based on a relatively small sample size of 89 respondents which may distort the results. Future research on this topic should be built on a broader database which enables more precise and refined results. Additionally, multiple surveys at different points in time would enable empirically validated statements on continuous usage. Lastly, the influence of gamification is only explained based on the distinction between gamification users and non-users. For future research, the differentiation between the four major gamification elements would allow for more detailed insights of the influence of gamification use. Additionally, coming research could combine the research on self-tracking motivations with the research on the user's perceptions about the characteristics of the self-tracking technology which might further increase the understanding of the phenomenon.

Generally, our research contributes to the domain of self-tracking and gamification as it advances the understanding how the usage of wearable self-tracking devices influences the user's perceived fulfillment of the initial motivations, and how gamification elements affect this interplay. Thereby, we found evidence that next to the motivation of increasing one's performance (Baumgart and Wiewiorra 2016), striving for self-entertainment is a key driver for using wearable self-tracking devices, and that the usage ultimately increases the perceived fulfillment of the user's motivations for self-entertainment, self-discipline as well as self-design. Furthermore, gamification elements might not support motivation fulfillment but rather distract users of wearable self-tracking devices from it. Our findings have three additional main practical implications: First, potential users of wearable self-tracking devices should be aware that self-tracking might help them to fulfill motivations which they have not previously been aware of. Second, we suggest that designers and manufacturers of wearable self-tracking devices consider addressing the entirety of motivational factors. This might improve their product attractiveness and let them reach more customers. Lastly, the use of gamification elements should be up to the user as their mandatory usage might not always support usage and motivation fulfillment.

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9. Appendix

Table 6: Cross Loadings

	Motivation for Self-Design	Motivation for Self-Discipline	Motivation for Self-Entertainment	Motivation for Self-Healing	Self-Design motivation fulfillment	Self-Discipline motivation fulfillment	Self-Entertainment motivation fulfillment	Self-Healing motivation fulfillment	Wearable self-tracking device usage
M-SDe1	0.773	0.309	0.338	0.326	0.597	0.280	0.248	0.257	0.134
M-SDe2	0.762	0.504	-0.073	0.227	0.625	0.390	0.008	0.225	0.161
M-SDe4	0.780	0.294	0.385	0.316	0.532	0.192	0.263	0.237	0.280
M-SDe5	0.772	0.623	-0.071	0.233	0.545	0.445	-0.015	0.129	0.243
M-SDi1	0.503	0.803	-0.023	-0.068	0.394	0.637	0.098	-0.027	0.071
M-SDi3	0.542	0.987	0.054	0.033	0.297	0.628	0.040	-0.099	0.264
M-SE1	0.279	0.209	0.641	0.330	0.278	0.220	0.620	0.365	0.162
M-SE2	0.192	0.120	0.742	0.095	0.153	0.139	0.527	0.153	0.259
M-SE3	0.030	-0.057	0.738	0.090	0.001	-0.022	0.429	0.125	0.192
M-SE5	0.091	-0.117	0.772	0.095	0.178	0.024	0.550	0.168	0.247
M-SH1	0.301	-0.043	0.085	0.820	0.142	-0.011	0.102	0.495	0.004
M-SH2	0.355	0.016	0.194	0.999	0.169	-0.013	0.132	0.455	0.050
GA-SDe1	0.619	0.207	0.366	0.184	0.760	0.422	0.432	0.434	0.195
GA-SDe2	0.516	0.312	0.001	0.080	0.820	0.578	0.221	0.355	0.221
GA-SDe4	0.564	0.076	0.276	0.247	0.719	0.201	0.405	0.424	0.292
GA-SDe5	0.555	0.447	0.006	0.007	0.786	0.633	0.166	0.189	0.269
GA-SDi1	0.307	0.495	0.142	-0.023	0.540	0.872	0.353	0.203	0.192
GA-SDi3	0.430	0.686	0.091	-0.006	0.548	0.965	0.198	0.134	0.357
GA-SE1	0.244	0.101	0.433	0.220	0.459	0.324	0.689	0.649	0.158
GA-SE2	0.143	0.123	0.567	0.034	0.215	0.201	0.822	0.271	0.249
GA-SE3	-0.016	-0.017	0.579	0.092	0.203	0.102	0.763	0.317	0.128
GA-SE5	0.087	-0.026	0.603	0.086	0.347	0.165	0.693	0.269	0.141
GA-SH1	0.260	-0.059	0.274	0.415	0.419	0.187	0.456	0.976	0.157
GA-SH2	0.249	-0.127	0.214	0.495	0.452	0.122	0.488	0.932	0.095
ST-Freq. Act.	0.245	0.299	0.219	-0.045	0.290	0.356	0.240	0.067	0.917
ST-Freq. Pas.	0.279	0.125	0.340	0.136	0.305	0.226	0.200	0.190	0.906