Electronic Markets (2021) 31:795–809
https://doi.org/10.1007/s12525-021-00458-3

RESEARCH PAPER

Understanding continued smartwatch usage: the role of emotional as well as health and fitness factors

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Received: 31 July 2020 / Accepted: 5 January 2021 / Published online: 18 February 2021

Abstract
Smartwatches are the most popular wearable device and increasingly subject to empirical research. In recent years, the focus has shifted from revealing determinants of smartwatch adoption to understanding factors that cause long-term usage. Despite their importance for personal fitness, health monitoring, and for achieving health and fitness goals, extant research on the continuous use intention of smartwatches mostly disregards health and fitness factors. Grounding on self-determination theory, this study addresses this gap and investigates the impact of health and fitness as well as positive and negative emotional factors encouraging or impeding consumers to continuously use smartwatches. We build upon the expectation-confirmation model (ECM) and extend it with emotional (device annoyance and enjoyment) as well as health and fitness factors (goal pursuit motivation and self-quantification behavior). We use structural equation modeling to validate our model based on 335 responses from actual smartwatch users. Results prove the applicability of the ECM to the smartwatch context and highlight the importance of self-quantification as a focal construct for explaining goal pursuit motivation, perceived usefulness, confirmation and device annoyance. Further, we identify device annoyance as an important barrier to continuous smartwatch use. Based on our results, we finally derive implications for researchers and practitioners alike.

Keywords Smartwatches · Continuance intention · Expectation-confirmation model · Self-determination theory · Self-quantification · Device annoyance

JEL classification I12

Introduction

Smartwatches are wearable devices which are equipped with a screen and sensors (e.g., accelerometers, IR sensors). A wireless connection to the internet on its own or through a smartphone allows to run proprietary as well as third-party apps (Nascimento et al. 2018). By increasingly meeting aesthetic demands, smartwatches straddle the line between technological device and fashion accessory. As smartwatches integrate functions of other wearables such as fitness trackers, they have the unique potential to address all three basic psychological needs postulated in self-determination theory (SDT) (Deci and Ryan 2000): autonomy, competence, and relatedness. Thus, it is not surprising that with 42% they take the lead in terms of end-user spendings on wearable devices in 2019 (Goasduff 2019). Projected 109.2 million global unit shipments of smartwatches in 2023 reveal the continued end-user demand and underline the economic importance of these devices. To date, Apple holds the largest share of the smartwatch market, followed by Samsung and Garmin (Ubrani et al. 2019).

For companies it is beneficial when their customers decide to continuously use their smartwatches. Not only will they be able to sell accessories (i.e., bands) and services (i.e., apps, abonnements, in-app purchases), but it is also guaranteed that follow-up models will be sold. Sustained smartwatch use, however, is not only desired by companies selling them, but there are indeed multiple parties which profit from long-term

This article is part of the Topical Collection on Digital Healthcare Services

Responsible Editor: Edith Maier

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use. By continuously wearing smartwatches, users benefit from the available functionalities, many of which are only possible because of the physical proximity and even skin contact. Smartwatches continuously monitor physiological parameters and daily activities, thereby encouraging individuals to live a healthier lifestyle, which will ultimately result in reduced health care expenses. Thus, long-term smartwatch usage for personal fitness and health monitoring is highly desirable on the individual level for end-users as well as on the macro-level for government and health insurance funds.

The importance of establishing prolonged smartwatch use calls for a deeper understanding of which mechanisms drive the continued use of smartwatches. We aim at furthering our knowledge in this domain by answering the following research questions:

> RQ1: In how far and through which mechanisms do health- and fitness-related factors drive the continuous smartwatch usage?
> RQ2: How do positive and negative emotional reactions affect the continuous smartwatch usage?

To answer these questions, we build upon the expectation-confirmation model (ECM) and develop an integrated framework explaining the continuance intention through positive and negative emotional as well as health- and fitness-related variables. Thereby, our study contributes to literature in the following ways. First, prior studies have mostly concentrated on investigating the adoption (e.g., Krey et al. 2019), purchase (e.g., Hsiao and Chen 2018), and behavioral intention to use (e.g., Choi and Kim 2016) wearables and smartwatches. Due to the benefits associated with long-term smartwatch use, in recent years, the focus has shifted towards understanding reasons for either abandoning fitness trackers (Attig and Franke 2020) and smartwatches (Shen et al. 2018) or continuously using them after initial adoption (e.g., Chuah 2019). We add to the last stream of literature by applying the ECM to the smartwatch context.

Second, despite their significant role in ongoing health monitoring, there is little academic research exploring how health- and fitness-related factors drive the continuance intention of smartwatches. Up to now, only Dehghani (2018) unveiled the importance of health factors for continuously using smartwatches by identifying healthtology, the importance of health factors for continuous smartwatch use, in his qualitative study.

By drawing on SDT, we argue that health- and fitness-related factors are particularly important for explaining why consumers continuously use smartwatches. Specifically, we introduce self-quantification and the new construct health and fitness goal pursuit motivation as important factors associated with continuous smartwatch use. Self-quantification, or self-tracking, belongs to the growing trend of self-optimization and refers to regularly gathering and subsequently analyzing health and fitness data (Lupton 2014). Thus, self-quantifiers draw on the functionalities of self-tracking devices such as smartwatches to generate insights about themselves. It becomes obvious that the self-quantification movement was only made possible by technological developments, which initiated the shift from niche to mainstream product (Day 2016) and which allow to precisely measure and track physiological data in everyday life.

In addition, psychologists emphasize the importance of goals and goal pursuit for understanding consumer choices (e.g., Kopetz et al. 2012). Research substantiated the importance of goal pursuit for health-related behavior (Benning et al. 2020). We argue that investigating the interplay of self-quantification and health and fitness goal pursuit motivation furthers our understanding of lasting smartwatch use.

Third, we contribute to literature by integrating emotional drivers of and barriers to continuous smartwatch usage. Prior research in this field considered positive emotional reactions towards smartwatches in terms of hedonic value (Hong et al. 2017), benefits (Chuah 2019), motivation (Dehghani et al. 2018), or as perceived enjoyment (Nascimento et al. 2018). So far, no research has incorporated negative emotional reactions elicited by smartwatch usage. We not only consider the positive emotion enjoyment but also introduce the novel construct device annoyance, which captures the feeling of being bothered by notifications of the smartwatch. By integrating annoyance elicited by smartwatch use, we address the discussed research gap and investigate how positive and negative emotional reactions affect the continuance intention.

The remainder of this paper is organized as follows. In the next section, we give an overview of the theoretical foundation and related research. Afterwards, we derive hypotheses and present the empirical validation of our model using covariance-based structural equation modeling (CB-SEM) on data from 335 actual smartwatch users. In the last section, we discuss our findings and implications and ultimately name potential limitations and future research directions.

Expectation-confirmation model

Theoretical background

Research has extensively used the technology acceptance model (TAM) to explain consumer intentions to adopt innovative technologies (Davis 1989). Due to the importance of repeated usage for the success of smartwatches, we draw upon the ECM, which has been established by Bhattacherjee (2001). Prior research proved its applicability to the contexts of social networks (Jin et al. 2009), personal IT devices (Chen 2014), and wearables (Nascimento et al. 2018). The ECM grounds on the TAM as well as the expectation-confirmation theory (ECT) as proposed by Oliver (1980). In contrast to the

TAM, the ECM focuses on post-usage rather than pre-usage expectations and posits that users' continuance intention is driven by satisfaction and perceived usefulness (Bhattacherjee 2001). While perceived usefulness captures pre-usage expectations in the TAM, in the ECM, it reflects the aggregation of long-term post-usage beliefs about the extent to which using a technology leads to higher performance, productivity, and effectiveness (Bhattacherjee 2001; Davis 1989). Satisfaction, defined as the user's assessment of feelings resulting from technology use, is driven by usefulness and confirmation. Confirmation describes the perceived congruence between expected use and actual performance and is hypothesized to also influence perceived usefulness (Bhattacherjee 2001). While the ECM has been widely used to explain the continuance intention for different technologies, research has also leveled criticism against it (Nascimento et al. 2018). One aspect which has been raised in prior literature is related to the fact that the ECM disregards the impact of motivational factors on continued IT usage (Sørebø et al. 2009). Another point of criticism regards the fact that emotional factors such as enjoyment might not only play an important role for the initial but also for the continued technology use (Thong et al. 2006). As these aspects provide fruitful avenues for extending and applying the expectation confirmation model to the context of smartwatches, we address these limitations by integrating positive and negative emotional factors as well as the goal pursuit motivation and self-quantification, two health- and fitness-related factors.

Self-determination theory

Deci and Ryan's SDT (Deci and Ryan 1985a; Deci and Ryan 2000) is a basic theory of human motivation. The theory posits that the intrinsic motivation to engage in a certain activity is determined by the degree to which this activity fulfils the three basic psychological needs: autonomy, competence, and relatedness (Deci and Ryan 2000). SDT has been previously used as a framework to explain the motivational impact of digital technologies on physical activities (Kerner and Goodyear 2017). Since smartwatches have the potential to fulfil all three basic psychological needs, we argue that SDT can be also consulted as an explanation for continued smartwatch use.

Smartwatch functions allow users to record their workouts and activity progress (e.g., through monitoring step count and calories burnt), to connect and share their achievements with others, to engage in competitions to earn awards, and to tailor their goals according to their needs. Thereby, smartwatches address the three basic psychological needs proposed in SDT. The need for competence is enhanced by feedback on physical activities. Smartwatches provide users with an increased sense of autonomy and empowerment by providing transparent health data which can be accessed and analyzed without having to consult a professional. Ultimately, smartwatches satisfy the need for relatedness through the embedded social features, which allow users to engage with others by for example sending them motivational or appreciating messages. As users experience a fulfillment of their basic psychological needs, they may develop self-determined motivations, associated with continuous smartwatch use, self-tracking, and engagement in physical activities (Teixeira et al. 2012).

Research on continuous use of smartwatches

To date, research on wearables mainly concentrated on the adoption intention of smartwatches (e.g., Chuah et al. 2016; Krey et al. 2019; Wu et al. 2016) and specific health and fitness devices (e.g., Gao et al. 2015). In contrast, we place the focus of our research on the continuous use intention of smartwatches. In Table 1, we provide a detailed analysis of this stream of research and outline how we contribute to current literature.

Hong et al. (2017) analyzed the impact of utilitarian and hedonic values based on a synthesis of theories. They showed that consumer innovativeness is positively associated with continuance use intention of smartwatches. By grounding on uses and gratification theory (U&GT), Cho and Lee (2017) used focus group and regression analysis to study the impact of practical and social factors on the continuance intention. Ensuing from theory of planned behavior (TPB), Song et al. (2018) showed that technology- and fashion-related factors enhance the attitude towards smartwatches. Their results further indicate that control-related factors indirectly affect the continuance intention through perceived behavioural control. Dehghani et al. (2018) demonstrated that the continuance intention is driven by operational imperfection, hedonic motivation, and aesthetic appeal. Further, Chuah (2019) established benefits and lifestyle incongruence as antecedents of continuance intention through inspiration and well-being.

In literature on continuous smartwatch use, only few studies based their research on the ECM despite its popularity in other realms. Among these, Ogbanufe and Gerhart (2018) investigated the indirect effects of utilitarian aspects (i.e., information and system quality) on continued use of smartphone features. While Pal et al. (2018) also addressed the utilitarian side of smartwatches by integrating perceived accuracy and functional limitations, they additionally studied the effect of hedonic motivation on continuous usage. They demonstrated a positive effect of perceived usefulness, hedonic motivation, perceived comfort, and self-socio motivation on continuous usage. Perceived privacy, battery-life concern as well as perceived accuracy and functional limitations were in contrast shown to negatively affect the continuance use of smartwatches. Nascimento et al. (2018) acknowledged both the hedonic and utilitarian side of smartwatches. Apart from habit, they introduced perceived usability, capturing the ease of use, and perceived enjoyment as antecedents of continuance intention. Very recently, Bölen

Table 1 Prior quantitative research on the continuance intention of smartwatches

Author(s)	Theoretical foundation	Technology	Research design	Constructs
Cho and Lee (2017)	U&GT	Smart devices	*N*=104 (hierarchical regression analysis)	Continuance Intention *Practical purposes:* Daily-Info Seeking, Disability-Info Seeking, Emergency Contact *Social purposes:* Amusement Seeking, Passing Time, Trendiness, Personal Relationships
Hong et al. (2017)	Integration of DIT, TAM, ECT & flow theory	Smartwatch	*N*=276 (CB-SEM)	Usage, Continuance Intention to Use Smartwatch, Hedonic Value, Utilitarian Value, Consumer Innovativeness
Ogbanufe and Gerhart (2018)	IS success model IS continuance model (ECM)	Smartwatch	*N*=295 (PLS-SEM)	Feature Use Continuance, System Satisfaction, Confirmation, Perceived Usefulness, Information Quality, System Quality (Perceived Convenience, Perceived Proximity, Haptics Feedback)
Song et al. (2018)	TPB	Smart-Connected Sports Products	*N*=322 (PLS-SEM)	Continuance Intention to Use, Attitude, Perceived Behavioral Control, Social Comparison, Technology-related Factor (Perceived Usefulness), Fashion-related Factors (Perceived Comfort, Fashion Aesthetics), Control-related Factors (Technical Functionality, Facilitating Conditions)
Dehghani et al. (2018)	–	Smartwatch	*N*=385 (PLS-SEM)	Continuance Intention, Healthology, Complementary Goods, Hedonic Motivation, Operational Imperfection, Aesthetic Appeal
Nascimento et al. (2018)	ECM	Smartwatch	*N*=574 (PLS-SEM)	Continuance Intention, Satisfaction, Confirmation, Perceived Usefulness, Habit, Perceived Usability, Perceived Enjoyment
Pal et al. (2018)	ECM	Smartwatch	*N*=312 (PLS-SEM)	Continuance Intention, Satisfaction, Confirmation, Perceived Usefulness, Hedonic Motivation, Perceived Accuracy & Functional Limitations, Perceived Comfort, Perceived Privacy, Battery-life Concern, Self-socio Motivation
Shen et al. (2018)	Expectation-Disconfirmation Theory	Wearable Health Information Systems	*N*=428 (PLS-SEM)	Intermittent Discontinuance (Breaks in Use, Controlled Use, Suspended Use), Neutral Satisfaction, Attitudinal Ambivalence, Neutral Disconfirmation
Cho et al. (2019)	S-O-R	Smartwatch	*N*=198 (PLS-SEM)	Product attachment, Interactivity, Autonomy, Visual Aesthetics, Self-Expression, Satisfaction, Pleasure
Chuah (2019)	–	Smartwatch	*N*=324 (PLS-SEM)	Continuance Intention, Inspiration, Well-Being (Physical, Psychological, and Social Relations Well-Being), Perceived Benefits (Utilitarian, Hedonic, Social, and Symbolic Benefits), Perceived Risks (Privacy and Physical Risks), Previous Lifestyle Incongruence

Table 1 (continued)

Author(s)	Theoretical foundation	Technology	Research design	Constructs
Bölen (2020)	ECM	Smartwatch	N=348 (CB-SEM)	Continuance Intention, Satisfaction, Confirmation, Perceived Usefulness, Perceived Aesthetics, Individual Mobility, Habit
Gupta et al. (2020)	ECM & Social Comparison Theory	Smart Fitness Wearables	N=684 (CB-SEM)	Intention to Recommend, Continuous Intention to Use, User Satisfaction, Confirmation, Perceived Usefulness, Perceived Health Outcomes, Social Comparison Tendency,
This study	ECM	Smartwatch	N=335 (CB-SEM)	Continuance Intention, Satisfaction, Confirmation, Perceived Usefulness, Enjoyment, Device Annoyance, Self-Quantification, Goal Pursuit Motivation

(2020) integrated individual mobility, habit, and perceived aesthetics to the ECM. Moreover, Gupta et al. (2020) investigated the indirect and direct impact of perceived health outcomes, the perceived benefits fitness wearables had on the own health, on the continuous intention to use smartwatches. The authors show that the backward-looking assessment of perceived health benefits increases satisfaction and continuance intention (Gupta et al. 2020).

Overall, previous literature on continuance intention disregards health and fitness factors as motivational variables. Drawing on SDT and the evermore emerging health and fitness trend, we, however, argue that these factors are required to satisfy the basic psychological needs and are thus important for explaining prolonged smartwatch usage.

Model development

To explain the continuance intention of smartwatches, we develop a new model by extending the ECM (Bhattacherjee 2001) with emotional as well as health- and fitness-related factors. Thereby, we are the first to integrate self-quantification behavior, goal pursuit motivation, and device annoyance into the ECM (Fig. 1).

The expectation-confirmation model In line with the assumptions of the ECM and prior research building upon the ECM to explain continuous smartwatch usage (e.g., Nascimento et al. 2018; Pal et al. 2018; Gupta et al. 2020), we derive our first five hypotheses:

H1: Satisfaction positively affects continuance intention.
H2–3: Confirmation positively affects satisfaction (H2) and perceived usefulness (H3).
H4–5: Perceived usefulness positively affects satisfaction (H4) and continuance intention (H5).

The influence of emotional factors According to SDT, extrinsic motivation describes the behavior driven by external achievements and rewards (Deci and Ryan 1985b), whereas intrinsic motivation refers to internal rewards, such as pleasure

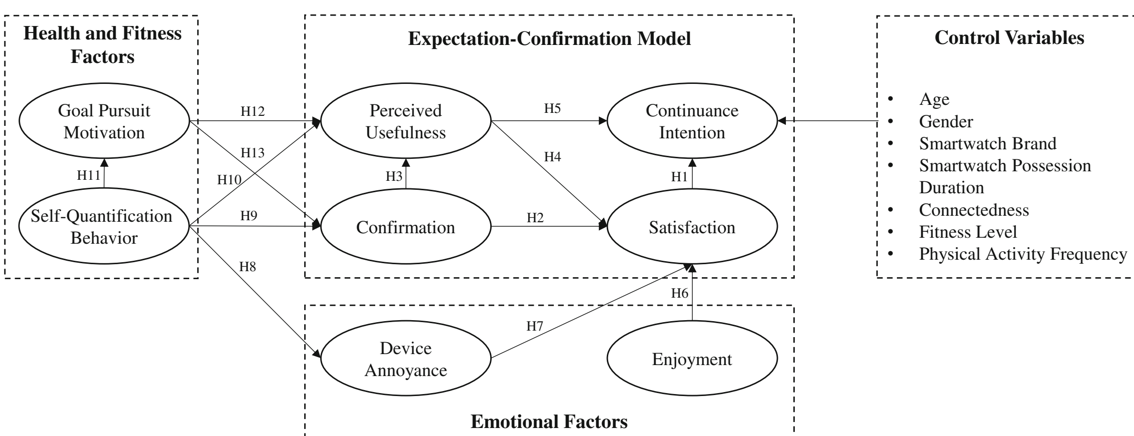

Fig. 1 Proposed model and hypotheses

and satisfaction of an activity (Deci 1971). In accordance with Venkatesh (2000), we define enjoyment as the degree to which the use of smartwatches is perceived as enjoyable in its own right. Enjoyment belongs to intrinsic motivations and arises when all three basic psychological needs are satisfied by the activity performed (Ryan et al. 2006). Within the research field of smartwatch adoption, Choi and Kim (2016) found a strong positive effect of perceived enjoyment on the attitude towards using a smartwatch. Krey et al. (2019) demonstrated that expected enjoyment indirectly over attitude enhances the smartwatch adoption intention. In terms of prior research on continued smartwatch usage, Pal et al. (2018) found enjoyment to significantly affect satisfaction and continuance intention, whereas in the study conducted by Nascimento et al. (2018) only the effect on satisfaction turned out significant. Based on these validated findings and the fact that satisfaction encompasses an assessment of feelings resulting from wearable usage, we hypothesize that enjoyment enhances smartwatch satisfaction.

H6: Enjoyment positively affects satisfaction.

Since smartwatches allow to quickly and easily view incoming messages with a glance at the small display, they are perceived as true wearables (Beh et al. 2019) and less intriguing than the larger smartphones. If the functionalities of the smartwatch are fully exhausted, they will not only give immediate feedback to trainings, but these electronic devices will use either tones or vibration as a signal for incoming calls or messages, app notifications, reminders to move, and training sessions completed by friends and family if connected. As users receive important and transparent information about their health and fitness, smartwatches satisfy the need for autonomy. Despite the benefits offered by smartwatches, the many interruptions through the course of a day might be perceived as bothering or irritating and will probably lead to device annoyance.

In an advertising context, Hutter et al. (2013) defined annoyance as an unpleasant emotional reaction to subjective overexposure to a certain kind of media. We argue that overexposure in a smartwatch context can result from the many interruptions and notifications of the smartwatch. Annoyance may arise only after some time of usage and potentially even mitigates the feeling of autonomy. Thus, if present, device annoyance leads to decreased satisfaction, resulting from the assessment of negative feelings arising from smartwatch use.

H7: Device annoyance negatively affects satisfaction.

The influence of health and fitness factors Consumers in the pursuit of fitness, health, and longevity increasingly engage themselves in self-quantification. The quantified-self movement describes the growing popularity of generating self-knowledge through self-tracking with "any kind of biological, physical, behavioral, or environmental information" (Swan 2013, p. 85). Following Maltseva and Lutz (2018), we define self-quantification as the process of collecting and reflecting on personal data by using smartwatches and self-tracking apps. Self-quantification mirrors a high involvement in physiological data collection and analysis. We posit that high self-quantifiers will be much more attached, probably even emotionally connected, to the technological device on their wrist and appreciate its notifications. Thus, they will be less annoyed by its functionalities and notifications about sport activities.

H8: Self-quantification behavior negatively affects device annoyance.

By quantifying themselves, users receive tailored analyses about their health conditions and physical activities. Research showed that health and fitness interest increases the adoption intention of wearable fitness trackers (Lee and Lee 2018). Individuals who are more physically active will more likely use fitness trackers as they perceive them as motivating (Rupp et al. 2018). Furthermore, Li et al. (2018) substantiated that the activity amount and frequency positively affect confirmation in the context of fitness-tracking apps. Since self-tracking is a core function of smartwatches, consumers who are interested in their health and fitness can use these devices for quantifying themselves. When doing so, they will experience smartwatches as precise and comprehensive measures of physiological and biological data. We conclude that self-quantification behavior increases confirmation as smartwatches allow these individuals to monitor their health as initially expected. Thus, we argue that individuals with a desire to quantify themselves will perceive a higher congruence between the expected and actual smartwatch performance (Bhattacherjee 2001).

H9: Self-quantification behavior positively affects confirmation.

Users who engage in self-quantification behavior habitually use smartwatches for quantifying themselves. Thereby, these users become increasingly familiar with the various functionalities provided by the smartwatches (Alsharo et al. 2020; Gefen 2003). As self-quantifiers are driven by the aim of experiencing greater self-understanding and self-improvement (DuFault and Schouten 2020), they will gain more advantages of the self-tracking functionalities of smartwatches. Consequently, they will regard them as highly useful technologies which help to increase their personal efficiency (Chuah et al. 2016).

H10: Self-quantification behavior positively affects perceived usefulness.

Furthermore, by automatically tracking and thus quantifying daily activities, smartwatches create an awareness of one's goals by making them and the individual progress towards these goals measurable. Drawing on qualitative findings, Pettinico and Milne (2017) argued that quantified results help users to focus on their goals and daily activities in pursuit of those goals. Also, Jarrahi et al. (2018) demonstrated that using fitness trackers could increase goal-directed behavior. In an empirical study, Zhang et al. (2019) showed that quantification induces greater goal pursuit motivation. Further, research has established that individuals who perceive themselves as closer to achieving a goal have a higher motivation to pursue the goal (Laran 2016). Therefore, we suppose that self-quantification leads to more transparent health data, which will enhance perceptions of health and fitness goal progress, and ultimately results in increased goal pursuit motivation.

> *H11: Self-quantification behavior positively affects goal pursuit motivation.*

We define goals as "internal representations of desired states" (Austin and Vancouver 1996, p. 338) and goal pursuit motivation as the extent to which an individual engages in a certain behavior to reach this desired end state (Laran 2016). Bagozzi and Edwards (1998) showed that goal intention increases activities of trying to reach one's goals and initiates goal-directed behaviors, which result in enhanced degree of goal attainment. Thus, we suppose that individuals with high health and fitness goal pursuit motivations will try harder to reach their goals by exercising regularly and living healthy to satisfy their need for competence. Furthermore, Laran (2016) substantiated that, in situations of conscious goal pursuit, individuals are aware of their goals and actively use feedback on their performance to plan subsequent behavior. Thus, when pursuing a healthy and active lifestyle, individuals use their smartwatches to attain feedback based on transparent and objective information provided by these wearable devices. Therefore, high goal pursuit motivation will enhance the perceived usefulness of the smartwatch for attaining health and fitness goals.

> *H12: Goal pursuit motivation positively affects perceived usefulness.*

We further hypothesize that goal pursuit motivation, which is driven by self-quantification behavior, also increases confirmation. We argue that by providing goal-related information, smartwatches provide individuals with information about their goal progress (Zhang et al. 2019), thereby supporting them in attaining their goals. Thus, goal pursuit motivation has a positive impact on the perceived congruence between the expected and actual performance of the smartwatch.

> *H13: Goal pursuit motivation positively affects confirmation.*

Research method

Instrument development and data collection

We mostly relied on established reflective multi-item measures to assess the latent constructs in our model. Specifically, scales for the constructs of the ECM (Bhattacherjee 2001;

Table 2 Detailed information about respondents

Characteristics	Number (n)	Percentage (%)
Sex		
Female	171	51.0
Male	164	49.0
Age groups		
18–24	64	19.1
25–34	161	48.1
35–44	34	10.1
45–54	40	11.9
55–64	30	9.0
65–75	6	1.8
Smartwatch brand		
Apple	205	61.2
Samsung	33	9.9
Huawei	4	1.2
Garmin	29	8.7
Fitbit	21	6.3
Xiaomi	14	4.2
Fossil	11	3.3
other	18	5.4
Smartwatch possession duration		
Less than one week	6	1.8
One week to one month	25	7.5
Two to six months	67	20.0
Seven to twelve months	59	17.6
More than twelve months	178	53.1
Connected with friends/family members		
Yes	75	22.4
No	260	77.6
Physical activity frequency		
Daily	24	7.2
Multiple times a week	185	55.2
Once a week	52	15.5
Multiple times a month	33	9.9
Once a month or less	41	12.2

Bhattacherjee and Lin 2015; Davis 1989), enjoyment (Venkatesh and Bala 2008), and self-quantification behavior (Maltseva and Lutz 2018) were adapted to the smartwatch context. Based on Hutter et al.'s (2013) annoyance scale, we developed a measure for device annoyance. Further, we extended the scale for goal pursuit motivation (Zhang et al. 2019) to capture both the motivation to exercise and to live a healthier life. Lastly, we included several control variables to account for individual differences. Besides age and sex, our participants were asked to indicate their smartwatch brand, the duration of smartwatch possession, and if they are connected with friends or family members via the smartwatch (dichotomous question). Additionally, we measured their fitness level with three items from Zhang et al. (2019), and asked how often they engage in physical activities (1 = daily; 5 = once a month or less). We measured all latent constructs on seven-point Likert scales ranging from 1 (strongly disagree) to 7 (strongly agree), except for satisfaction, which we assessed on a five-point semantic differential scale.

Data were collected through a questionnaire, which we administered online in November and December 2019. As respondents, we recruited 335 German smartwatch users ($M_{age} = 34.45$, $SD = 12.42$) of which 90.7% had owned a smartwatch for at least two months. As our sample varied in terms of smartwatch use duration and intensity, we do not expect that sample bias alters our results. Table 2 provides a detailed overview of the study's respondents.

Measurement model assessment

Prior to testing the hypothesized relationships, we assessed the adequacy of the measurement model. Given the substantial changes we made to the established scale of goal pursuit motivation to capture both health and fitness goal pursuit, we conducted an exploratory factor analysis (EFA) on this scale. The EFA indicated a Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of .89, exceeding the critical value of .60 (Kaiser 1970; Kaiser and Rice 1974). In addition, the results of Bartlett's test of sphericity (Bartlett 1951) verified the sampling adequacy of the data set for factorability ($p < .001$). A scree plot of eigenvalues implied a one-factor solution to be most appropriate for measuring goal pursuit motivation. Furthermore, each measurement item achieved a factor loading above .84 and a communality value above .71, exceeding the recommended value of .40 (Field 2005). Finally, the corrected item-total correlation coefficients ranged from .82 to .88, indicating high homogeneity of the items. Summarizing, the results of the EFA show that we can include goal pursuit motivation in our further analysis.

Subsequently, we employed CB-SEM through R and the package lavaan (Rosseel 2012) to test the measurement and structural model. Since prior analysis showed that multivariate normality of the variables is not given, we applied a maximum likelihood estimation with robust standard errors and a mean-adjusted chi-square test statistic (MLM; Rosseel 2012). This procedure, which is also referred to as Satorra-Bentler chi-square test, introduces a scaling factor to the test statistics (Satorra and Bentler 1994). Simulation studies have shown that Satorra-Bentler scaled test statistics yield more accurate results than standard maximum likelihood estimators when the distribution of scores deviates from a normal distribution (Boomsma and Hoogland 2001).

In CB-SEM, no absolute standard regarding adequate sample size exists. However, our sample fulfils some general recommendations. The sample size of 335 is larger than the often-recommended size of $N = 200$ (Boomsma and Hoogland 2001). Further, the general rule of thumb to have 10 times the number of respondents as items (Kline 2011) is fulfilled because the ratio of cases to indicators is 10.8:1. Thus, we reason that the current sample is deemed suitable for analyzing the proposed model. Table 3 provides an overview of the measurement model assessment.

We achieved construct reliability and validity since, for each scale, Cronbach's alpha is above .70 (Nunnally 1978), composite reliability (C.R.) is greater than .70, and average variance extracted (AVE) is above .50 (Hair et al. 2014). Overall high factor loadings prove the applicability of the scales. The results of the confirmatory factor analysis (CFA) provide evidence for construct validity and *goodness of fit* in the data[1]: $\chi^2/df = 1.88$, Comparative Fit Index (CFI) = .946, Tucker-Lewis Index (TLI) = .939, Root Mean Square Error of Approximation (RMSEA) = .058, Standardized Root Mean Square Residual (SRMR) = .048.

Following the CFA, we conducted further analyses to establish discriminant validity. As shown in Table 4, discriminant validity is achieved since the AVE values, which are shown below the diagonal, exceed the squared correlations between the relevant factors (Fornell and Larcker 1981). Further, the values for the heterotrait-monotrait ratio (HTMT), which are shown above the diagonal, are well below the threshold value of .85 (Henseler et al. 2015).

Common method bias

As the data of our study is self-reported, we used procedural as well as statistical remedies to control for common method bias (CMB). First, we randomized the order of the questions in the online questionnaire. Second, we conducted Harman's single factor test with an unrotated factor solution (Podsakoff et al. 2003), which showed that the single factor explained <50% of variance (38%). Third, we followed Eichhorn (2014) and included a common latent factor in the CFA. The model indicates that the factor explains 27% ($R = .54^2$) of variance. Lastly, we conducted the common

[1] Following Brosseau-Liard et al. (2012), Brosseau-Liard and Savalei (2014), and Savalei (2018), we report the new robust goodness of fit values.

Table 3 Instrument reliability and validity

Constructs and items	Stand. Loadings	α	C.R.	AVE
Continuance Intention (Bhattacherjee 2001)		.942	.945	.851
I intend to continue using my smartwatch rather than discontinue its use.	.844			
I predict I would continue using my smartwatch.	.962			
I plan to continue using my smartwatch.	.958			
Usefulness (Bhattacherjee and Lin 2015; Davis 1989)		.908	.913	.739
Using my smartwatch improves my performance.	.845			
Using my smartwatch increases my productivity.	.901			
Using my smartwatch enhances my effectiveness.	.936			
I find my smartwatch to be useful.	.708			
Satisfaction (Bhattacherjee 2001)		.899	.904	.694
How do you feel about your overall experience of smartwatch use?				
Very dissatisfied/very satisfied	.768			
Very displeased/very pleased	.876			
Very frustrated/very contented	.865			
Absolutely terrible/absolutely delighted	.837			
Confirmation (Bhattacherjee 2001)		.828	.832	.626
My experience with using the smartwatch was better than what I expected.	.804			
The functions provided by the smartwatch were better than what I expected.	.822			
Overall, most of my expectations from using the smartwatch were confirmed.	.738			
Enjoyment (Venkatesh and Bala 2008)		.864	.872	.690
I find using the smartwatch to be enjoyable.	.775			
The actual process of using the smartwatch is pleasant.	.801			
I have fun using the smartwatch.	.920			
Self-Quantification (Maltseva and Lutz 2018)		.929	.929	.725
I regularly collect data on my behavior using self-tracking devices.	.889			
It is important for me to collect data on my behavior.	.861			
I monitor my collected data regularly.	.834			
I analyze my data regularly.	.836			
I make connections between my behavior and the data that I get from self-tracking devices.	.833			
Device Annoyance (developed based on Hutter et al. 2013*)* I think it is disturbing if...		.747	.767	.514
… my smartwatch asks me to exercise.	.774			
… my smartwatch sends me motivational messages.	.846			
… my smartwatch informs me about my friends' sport activities.	.528			
Goal pursuit Motivation (adapted from Zhang et al. 2019*)*		.954	.952	.768
Using my smartwatch keeps me motivated to exercise regularly.	.845			
Using my smartwatch pushes me to increase the effort I put toward exercising.	.798			
Using my smartwatch motivates me to exercise harder than I have in the past.	.820			
Using my smartwatch keeps me motivated to live healthier.	.927			
Using my smartwatch, motivates me to work towards a healthier lifestyle.	.930			
Using my smartwatch motivates me to live healthier than in the past.	.931			

marker variable approach. To do so, we included social desirability, which we measured with a short version of the Marlowe-Crowne Social Desirability Scale (Crowne and Marlowe 1960; Fischer and Fick 1993), as the common marker variable and also included a latent factor, as explained above. Results of the common marker variable approach imply that the common variance amounts to 5.29% ($R = .23^2$). Based on the results of the three statistical tests, we conclude that common method bias is no serious threat in this study.

Results

As for the CFA, we employed a maximum likelihood estimation with robust standard errors to estimate the full model (Satorra and Bentler 1994). Since all robust indices for the overall fit have appropriate values (χ^2/df = 2.03, CFI = .935, TLI = .928, RMSEA = .063, SRMR = .088), the hypothesized model is considered acceptable.

As outlined in Fig. 2, all hypotheses are supported. Regarding the ECM, results imply that satisfaction is a strong driver of continuance intention (H1, β = .500, $p \leq .001$). Further, confirmation was found to be a significant driver of both satisfaction (H2, β = .507, $p \leq .001$) and perceived usefulness (H3, β = .255, $p \leq .001$). Perceived usefulness in turn shows a significant positive effect on satisfaction (H4, β = .161, $p \leq .01$) and continuance intention (H5, β = .160, $p \leq .01$). Results for the integrated emotional factors imply that perceived enjoyment has a significant positive (H6; β = .351, $p \leq .001$) and device annoyance a significant negative impact (H7; β = −.100, $p \leq .05$) on satisfaction. In terms of the health and fitness factors, self-quantification behavior was found to significantly reduce device annoyance (H8, β = −.243, $p \leq .001$) and to increase confirmation (H9, β = .192, $p \leq .05$), perceived usefulness (H10, β = .227, $p \leq .001$), and goal pursuit motivation (H11, β = .544, $p \leq .001$). The latter exerts a positive effect on perceived usefulness (H12, β = .464, $p \leq .001$) and confirmation (H13, β = .243, $p \leq .01$). Overall, the model has an appropriate predictive power for perceived usefulness (R^2 = .57), satisfaction (R^2 = .58), and continuance intention (R^2 = .35), emphasizing the relevance of the proposed emotional as well as health and fitness factors.

To assess the robustness of our results, we integrated the control variables age, sex, smartwatch brand, duration of smartwatch possession, connectedness with friends and family members, and fitness level. After including these control variables into the model, the results remained stable. Only the effect of age on continuance intention was positive and significant (β = .111, $p \leq .01$), indicating that older participants have a higher intention to continuously use smartwatches.

Discussion of results

The primary focus of the present paper is to further our knowledge in the domain of continued smartwatch usage. Specifically, we aimed at a) identifying the mechanisms through which health- and fitness-related factors drive the continuous smartwatch usage and b) understanding how positive and negative emotional reactions affect the continuous smartwatch usage.

The results confirm all relationships proposed in the ECM and thereby provide support for previous research on continuance intention of smartwatches (Nascimento et al. 2018; Ogbanufe and Gerhart 2018; Pal et al. 2018). Thus, we once more show the applicability of the ECM to the smartwatch context. In contrast to the results obtained by Bölen (2020) and Gupta et al. (2020), but in line with the ECM, we provide evidence that perceived usefulness significantly increases continuance intention. These results underline that continuous smartwatch use is not only driven by hedonic (Dehghani et al. 2018), but also by utilitarian aspects. This is especially true for individuals who aim at quantifying themselves with the goal of reaching health- and fitness-related goals.

Regarding the impact of health and fitness factors, the results show a highly significant impact of self-quantification on usefulness. This corroborates research on health information systems showing that habitually using a technology increases familiarity with its functionalities and thus usefulness (Alsharo et al. 2020). Moreover, the results indicate that self-quantification positively affects confirmation. Since those who are physically active will more likely use fitness trackers (Rupp et al. 2018), our research extends previous findings that the activity amount and frequency positively affect

Table 4 Results of Fornell-Larcker criterion and heterotrait-monotrait ratio

	1	2	3	4	5	6	7	8
Continuance Intention (1)	***.851***	.515	.590	.517	.594	.378	.241	.264
Usefulness (2)	.190	***.739***	.571	.539	.475	.587	.259	.686
Satisfaction (3)	.340	.286	***.694***	.730	.625	.409	.261	.389
Confirmation (4)	.242	.241	.493	***.626***	.520	.322	.110	.365
Enjoyment (5)	.334	.190	.364	.240	***.690***	.336	.261	.278
Self-Quantification (6)	.133	.305	.163	.095	.110	***.725***	.255	.540
Device Annoyance (7)	.050	.044	.057	.010	.058	.053	***.514***	.216
Goal pursuit Motivation (8)	.071	.458	.147	.122	.071	.292	.050	***.768***

AVE values are shown in italic in the diagonal. Squared correlation values are shown below the diagonal. HTMT values are displayed above the diagonal (here the threshold value of .85 applies) confirmation (Li et al. 2018). Furthermore, in line with previous qualitative (Pettinico and Milne 2017) and quantitative research (Zhang et al. 2019), we demonstrate that self-quantification itself has a strong impact on goal pursuit motivation. This underlines that self-tracking produces performance feedback and thus enhances the users' motivation to pursue their goals (Zhang et al. 2019). Thus, self-quantification enhances the perception that goals are attainable. These results provide support for the notion that smartwatches should not only be regarded as a technological gimmick. Instead, they can intrinsically motivate users to increase their physical activity and help boosting their health conditions.

We observe a strong and significant effect of goal pursuit motivation on perceived usefulness. This effect implies that individuals with high health and fitness goal pursuit motivations value the smartwatch as a useful technology that helps them achieving their goals by providing feedback (Laran 2016). The significant impact of goal pursuit motivation on confirmation further proves that individuals who are motivated by smartwatches to exercise regularly and live healthy perceive a higher congruence between the expected and actual performance of the smartwatch. Thereby, we extend current literature on fitness tracking devices which is limited to analyzing the antecedents of goal pursuit motivation (Zhang et al. 2019).

Concerning the effects of emotional factors, the results provide evidence for a strong and highly significant impact of enjoyment on satisfaction. Thus, we corroborate prior smartwatch research. Previous studies demonstrated that users who perceive smartwatches as enjoyable have more positive attitudes towards (Choi and Kim 2016; Krey et al. 2019) and are more satisfied with these devices (Nascimento et al. 2018; Pal et al. 2018). In contrast, device annoyance has not been studied so far. The effect of device annoyance on satisfaction is significant ($p \leq .05$) but not as strong and highly significant as the effect of enjoyment. As we observe that self-quantification exerts a strong negative impact on device annoyance, we conclude that those individuals who regularly quantify themselves appreciate the notifications of the smartwatch and device annoyance is thus less likely to arise. While the observed results reduce the potential negative effects of device annoyance, it is still important to note that annoyance may arise from the many interruptions and notifications of the smartwatch and that individuals who perceive device annoyance potentially perceive using the smartwatch as less satisfying. In summary, we confirm previous results on enjoyment and additionally identify device annoyance as an important barrier to smartwatch satisfaction and thus relevant for sustained smartwatch use.

Theoretical contribution

Smartwatches belong to the most popular wearable devices and have thus received increasing academic interest over the last couple of years. Lately, the focus has shifted from studying determinants of smartwatch adoption to understanding the drivers and barriers of continued smartwatch usage. Research in this field, however, is still in its infancy and more knowledge regarding the role of health- and fitness-related factors in explaining long-term usage is required. We contribute to literature by (1) providing support for the applicability of the ECM to smart

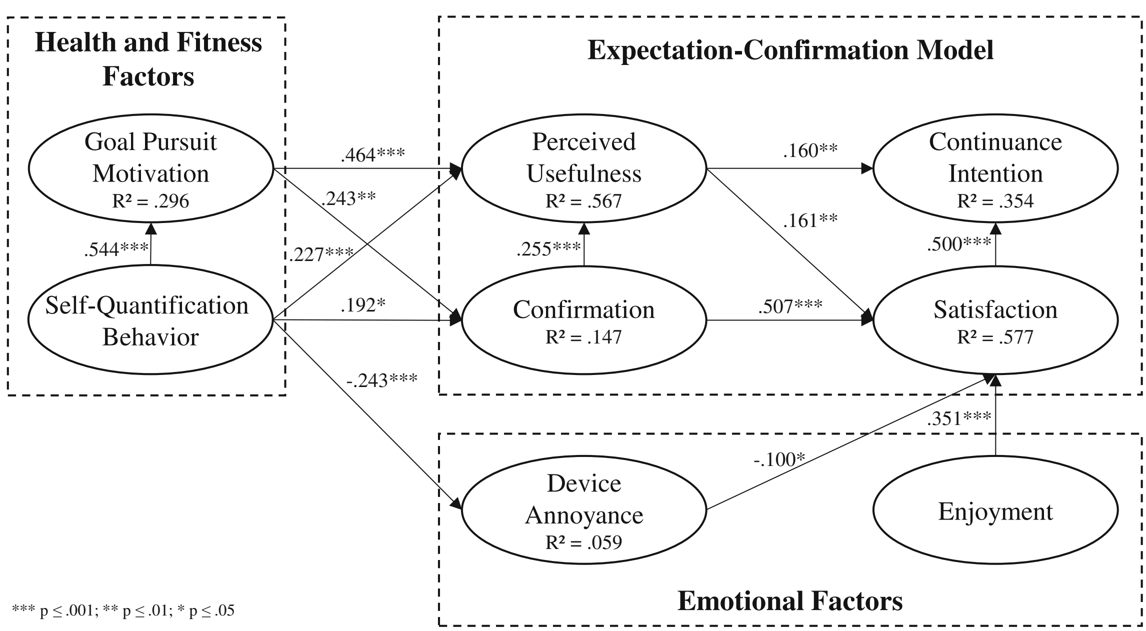

Fig. 2 Structural equation modeling results

connected devices and especially smartwatches, (2) integrating two relevant health- and fitness-related constructs which have not been studied in the context of continuous smartwatch use before, and (3) revealing emotional drivers of and barriers to continuous smartwatch usage.

First, we add to the development of research on continued use of smartwatches. Current literature on wearables mainly focused on the adoption (e.g., Krey et al. 2019) or behavioral intention (e.g., Choi and Kim 2016) to use smartwatches or health and fitness wearables rather than on the continuance intention of smartwatches (e.g., Hong et al. 2017). By concentrating on the continued use of smartwatches, we address the increasing demand for establishing long-term usage to ensure revenues and to increase positive health benefits for users.

Second, we generate interesting novel insights from the interplay of the two health- and fitness-related constructs self-quantification behavior and goal pursuit motivation and their impact on long-term smartwatch use. Results confirm that self-quantification and goal pursuit motivation are both important antecedents of perceived usefulness and satisfaction. Further, we can determine self-quantification as a driver of goal pursuit motivation.

Third, we show that apart from usefulness and confirmation, resulting from a rational assessment of a smartwatch, also emotional factors significantly affect smartwatch satisfaction. By integrating enjoyment and device annoyance into our model, we equally address the impact of positive and negative emotional variables on smartwatch satisfaction. While we identify enjoyment as a driver of satisfaction, device annoyance is established as a barrier to satisfaction.

In addition to the points discussed above, this study contributes to IS research by bridging the gap between behavioral and design science research. Typically, design science and behavioral science are viewed as distinct research paradigms (Wimmer and Yoon 2017). Design science understands research as building and evaluating artefacts which target certain real-world problems, whereas behavioral science rather concentrates on developing and testing theories (Hevner et al. 2004). Both approaches, however, should be viewed as complementary (Wimmer and Yoon 2017). We combine design and behavioral science research as we test established theories which explore the underlying mechanisms constituting continuance intention. Further, we extend traditional theories with elements that help developers to design solutions (Hevner et al. 2004) to further increase the continued usage.

In summary, by developing an integrative framework containing established and novel emotional as well as health and fitness factors, we contribute to current literature and provide insights into the psychological mechanisms translating perceived benefits into outcomes relevant for government, healthcare, academics, and industry.

Managerial implications

Based on our results, we can derive implications for several recipients. Since government and health insurance funds benefit from a healthy population, they could support smartwatch purchases to help users achieve their fitness goals and in turn save treatment costs. Our research shows that individuals who engage in self-quantification have an increased motivation to pursue their health and fitness goals, indicating a higher intention to engage in physical activities. As smartwatch adoption and initial use does not automatically imply that users engage in self-quantification, they should be shown and taught how they can use the functionalities provided by the watch and the possibility to track data. Moreover, we recommend that marketers highlight the benefits for health and fitness associated with smartwatches in their advertising campaigns. The importance of engaging users in self-quantification is further established by our research which shows that self-quantification significantly reduces device annoyance, the negative emotional reaction elicited by receiving bothering messages. Since device annoyance is a strong inhibitor of satisfaction, companies should concentrate on reducing or even preventing this negative emotional reaction towards smartwatches to increase satisfaction and in turn continuance intention. Apart from engaging users in self-quantification, another possibility to mitigate annoyance is related to the functionalities of the smartwatch itself. Given the fact that annoyance may arise from interruptions of the smartwatch, companies should include easily accessible menus allowing users to customize their smartwatch notifications according to their needs. Furthermore, based on the fact that enjoyment significantly enhances satisfaction, we suggest that marketers should emphasize the hedonic side of smartwatches along their utilitarian aspects.

Limitations and future research

Our research has some limitations that warrant future research. In our study, we explicitly considered smartwatch characteristics addressing the two basic psychological needs of autonomy and competence. Smartwatches also touch upon the need for relatedness as they enable users to connect and interact with friends and family members. Due to the importance of fulfilling the three basic psychological needs, we suggest placing special emphasis on the social component of smartwatches in future research. Given the fact that age evokes a significant effect on continuous intention, it might be interesting to assess age-related differences more deeply. To further evaluate the generalizability of our model, we propose replicating our study with a culturally more diverse sample. Also, we suggest applying our model in the context of other wearable devices such as activity trackers. There, special emphasis should be placed on the newly established construct device annoyance, which might also be a barrier to the success of other smart devices.

Wearables are associated with data security and privacy concerns owing to the sensitive information which they continuously collect and store (Motti and Caine 2015). Qualitative research identified health information privacy concerns as barrier to wearable health technology growth (Becker 2018). While one would generally assume that these concerns impose greater threat to initial wearable adoption, research has demonstrated that data vulnerability grows over time as userbase increases (Biswas and Mukhopadhyay 2018). If software becomes more vulnerable to cyber-attacks over time, it might be a fruitful avenue for future research to assess the impact of privacy concerns on continuous smartwatch usage.

Noting that smartwatches can elicit status through aesthetic design and better athletic appearance, future research should further examine internal and external motives for continued use. Despite the discussed limitations, we provide a first systematic understanding of the impact of positive and negative emotional as well as health- and fitness-related factors on continuous smartwatch use.

Funding Open Access funding enabled and organized by Projekt DEAL.

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