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RESEARCH PAPER

Smart services in healthcare: A risk-benefit-analysis of pay-as-you-live services from customer perspective in Germany

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Abstract The recent boom in wearable technologies generates enormous vital data sets, which are the ideal starting point for new service offers by Big Data Analytics. In a Pay-As-You-Live (PAYL) service, insured track activities, transfer current data on the lifestyles of users, who receive rewards from their insurance companies. The aim of this study is to investigate the readiness of customers to adopt PAYL services using wearable technology by comparing perceived privacy risks and perceived benefits. The research model is developed on a basis of a literature review and expert interviews. By conducting an online survey involving 353 participants, a structural equation modelling approach is used to test the research model. The results show that current privacy risk factors dominate the perceived value of an individual to use PAYL services. Insurance companies, service providers and manufacturers of wearables must therefore primarily work together and offer solutions for greater data security and data protection before focusing on gamification and functional congruence.

Keywords Pay-As-You-Live service · Wearable technologies · perceived privacy risk · perceived benefit · intention to use

JEL Classification L86

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Introduction

Developments over the past few years have shown that an increasing number of products are becoming "smart", e.g. the fitness belt animates us to do more exercise, the refrigerator orders food independently. With regard to this consumer-generated data, for example, health insurance companies are interested in subsidizing the purchase of fitness bracelets and setting up bonus programs (Kolany-Raiser 2016). Additionally, more and more health oriented people record their fitness and health data using wearable technology (Berglund et al. 2016). The trend of self-monitoring (quantified self) and the corresponding growth of the wearables market, are increasingly developing a mass market with a projected market size of over 34 billion US dollars and with anticipated sales of 411 million smart wearables in 2020 (CSS Insight 2016). These devices range from activity trackers (e.g. Fitbit, Jawbone) and Google Glasses to smart clothing (e.g. biometric shirts) which track steps, heart rate or physical activity. People wearing wearables generate a large amount of health data through their daily routine rather than by excessive sport performance (Sultan 2015). Due to increasing digitization, insurance companies can most notably use these emerging technologies to promote preventive healthcare measurements while simultaneously introducing smart services and reward systems (Rundshagen 2015). Smart services are a combination of physical and digital value-added services based on smart products like wearables (Wei 2014). Smart services rely on large quantities of aggregated data provided by smart/intelligent products (Allmendinger and Lombreglia 2005). For example, Generali recently introduced "Vitality", a new service structure based on data collected from wearable devices that encourage healthy behaviour with all kind of rewards. The service is designed to cover life-insurance, disability-insurance and health-insurance. This is intended to motivate customers by rewarding their progress and providing them with information on a health-conscious life. In general, this insurance service is called Pay-as-you-live (PAYL). Insured persons are expected to transfer current data about their lifestyle to the insurer through existing and new data sources, such as wearables (Ernst & Young 2015, PWC 2016). PAYL services may bring about new innovative product solutions in the insurance industry that increase the benefits for the insured individual by way of cheaper premiums or discounts. The insurance company itself can benefit from a lower claims expenses due to an improved lifestyle, which in turn is funded by lower premiums rewards. Therefore, the idea of collective insurance increasingly differs from the consideration of individual risks due to technological opportunities and changing customer requirements. According to a representative survey by BITKOM (2015), 31% of citizens aged 14 years and older use so-called fitness trackers for recording health values: 18% use fitness bracelets, 13% smartphones with fitness apps and 6% smartwatches. Moreover, 33% of all interviewed persons would be willing to provide their insurance company with their personal collected data. However, 39% of the respondents were found to have concerns and would not be willing to submit their sensitive health data. Therefore, it is important for insurance companies to know how such a service must be designed to be used by many. As shown by Alt (2016) each form of customer-orientation has individual characteristics that need to be assessed in order to offer the best service to customers and to strive for maximum customer satisfaction and/or experience. To date, most studies discuss the potential chances and challenges of wearable technology usage and suggest that insurance companies should make use of emerging technology trends such as smartphones, fitness apps and wearables to estimate the health risks of their insurants (Nürnberg 2015, Rundshagen 2015). Most studies were conducted to investigate technological aspects and wearable technology adoption (Yang et al. 2016, Gao et al. 2015). However, little research has been carried out to examine the potential of smart services such as PAYL using wearable technology.

Therefore, the purpose of this paper is to analyze the adoption of wearable technologies for the usage of PAYL services by conducting an empirical quantitative survey in Germany based on an adapted technology acceptance model. The aim is to investigate customer needs in order to derive recommendations for insurance companies. In our study, we focus on the privacy calculus theory (PCT) of Culnan and Armstrong (1999) as an extended risk-benefit analysis. More specifically, antecedents of perceived privacy risk are compared with antecedents of perceived benefits to calculate a person's perceived value (Yang et al. 2016) and the intention to use wearables for PAYL services. As privacy concerns have been identified as the main factor that impacts the intention of costumers to adopt and use wearable technology (Gu et al. 2015, Gao et al. 2015; Ernst and Ernst 2016), we propose to analyze the perceived privacy concerns of PCT for PAYL services using mobile user information privacy concerns (MUIPC) as an important predictor. MUIPC is measured using three dimensions: errors (Stewart and Segars 2002), perceived intrusion, and secondary use of personal information (Xu et al. 2012). In contrast to risk analysis, perceived benefit is analyzed using different dimensions from the unified theory of acceptance and use of technology 2 (UTAUT 2) (Venkatesh et al. 2012). Before the quantitative survey was carried out, qualitative interviews with experts from different insurance companies were conducted in order to gain a deeper insight into PAYL services, their usage in the insurance industry and the factors influencing the intention to use. This paper makes a theoretical contribution by conceptualizing that the privacy concerns of mobile users noticeably affect perceived privacy risks when using wearable technology for healthcare purposes. An increasing number of studies in IS research, investigate wearable technology from the adoption, technical and security perspective. However, a review of the literature suggests that an investigation of the influence of perceived privacy risks compared to the perceived benefits of PAYL services using wearable technology has not yet been carried out. Additionally, the direct added relationship of MUIPC to PCT has not been tested before. This paper aims to fill this research gap. The overall results might help to explain how to attract, expand and retain customers in order to derive greater value from new and existing relationships by utilizing PAYL services in the course of the increasing digitization and distribution of smart services. Against this background, it is proposed to answer the following research question by combining qualitative and quantitative data:

> **RQ: How do perceived privacy risk and perceived benefit influence the intention to use Pay-As-You-Live services using wearable technologies?**

The remainder of this study is organized as follows. The next section focusses on the theoretical background of this paper. We then conceptualize the research model and propose our hypotheses. The subsequent section describes the research methodology, followed by a section describing the data analysis and the results of this study. Finally, we discuss the implications of our research, give recommendations in terms of theoretical and practical contributions, and provide a conclusion.

Theoretical background

Literature Review

In order to provide a holistic overview of current research in the field of wearable technology and PAYL services, a literature research was conducted. According to Webster and Watson (2002), effective literary research can provide a solid foundation for additional knowledge and facilitate the development of theoretical aspects. This includes areas in which a wealth of research already exists and covers fields in which where research is still required. The methodology underlying this study is based on the structured approach according to Webster and Watson (2002). The term "smart services" encompasses data and service-based offers, such as mobile applications, online portals, and sharing services. Smart services are based on the increasing intelligence of machines and a complete digitization of work processes (Kagermann et al. 2014, Allmendinger and Lombreglia 2005). This allows companies to offer their customers higher-quality and more targeted services. At the same time, cloud-based platforms simplify the development, provision and controlling of services. Smart services interconnect Internet services and physical services. In so doing, existing and newly-acquired data are processed on a smart service platform and are incorporated into the smart service (Bauer 2015). The processed data can be personal fitness and wellness data, mobility data, medical surveillance data or data relating to other areas of daily life. Smart and successful services are context-oriented and need-oriented, often personalized and available anywhere (Leimeister et al. 2014). Pay-as-you-live (PAYL) is the gateway to new digital business models and risk assessments for insurance companies. Networking, big data and the trend towards self-optimization provide an almost revolutionary breakthrough in the industry. Through the evaluation of vital and behavioral data, completely new mobile services and tariff models will be created (Schröder and Schloss 2015). Similar to the pay-as-you-drive insurance, customers will be rewarded for a certain behavior. The opportunities are indeed huge - but the challenges as well (Kolany-Raiser 2016). In a PAYL service, an insurance company rewards its policyholders for a healthy lifestyle (Ernst & Young 2015, PwC 2016) and may reduce the high costs of insurance companies, resulting from chronic diseases (Eduard 2007). The insured person decides whether he wants to convey current data about his lifestyle (fitness, nutrition, sleep, etc.) through wearables (smartphones, smartwatches, fitness-bracelets, etc.) to a service provider. Besides activity trackers, such as Jawbone, Fitbit, and Goodon, etc., smartwatches, scales, blood pressure monitors and even smartphones can be considered as wearables as they are worn close to the body and are equipped with the necessary technology to collect and collect data on health and fitness condition (Chen and Shih 2014). The service provider calculates a health score from the health and lifestyle data and transmits it to the insurance company. If the insurant improves his behavior (attains a lower risk class), he can reduce his insurance tariff premium or receive earned points to gain rewards in the form of discounts, bonuses, health advice or other gratifications (Nürnberg 2015). Figure 1 shows the PAYL service process.

Recent studies have investigated wearable technology adoption from the user perspective, focusing mainly on technological aspects or the use of wearables for healthcare purposes (Yang et al. 2016, Li et al. 2016, Gao et al. 2015, Yoon et al. 2015, Kim and Shin 2015). Privacy risks have been identified as the main factor that affects the intention of a consumer to adopt and use wearable technology (Gu et al. 2015, Gao et al. 2015; Ernst and Ernst 2016). While Gao et al. (2015) propose an integrated model, which takes health, technological and privacy issues into account, and differentiates between fitness and medical services, Kim and Shin (2015) not only consider technological aspects but also key psychological determinants of smartwatch adoption such as relative advantage or subcultural appeal. Pfeiffer et al. (2016) and Chen and Shih (2014) explore the factors affecting the acceptance of wearable technology with a focus on pre-adoption criteria. Interestingly, Pfeiffer et al. (2016) found that the perceived support of health and fitness has no influence on the intention to use wearable self-tracking technology. Both Yoon et al. (2015) and Boontarig et al. (2012) investigate the intention to use wearables for preventive health services. Boontarig et al. (2012) focus on the factors which influence the intention of elderly Thai people to use smartphones for e-health services. It is striking that perceived value has a strong influence on the intention of elderly people to use smartphones as well as on facilitating conditions and effort expectancy. In contrast, Yoon et al. (2015) investigate the use of smartwatches as a preventive health tool, focusing on information tailoring and data privacy. The majority of their qualitative study reports on the potential value of a smartwatch for managing physical conditions on a daily basis. Previous studies examining the intention to use wearables were conducted in Asia (Gao et al. 2015, Chen and Shih 2014, Boontarig et al. 2012, Yoon et al. 2015), the US (Yuan et al. 2015, Kim and Shin 2015), Turkey (Turhan 2013) and Germany (Pfeiffer et al. 2016; Ernst and Ernst 2016). However, a risk-benefit-analysis of the use of wearable technology for PAYL services from the customer perspective to derive recommendations has not yet been conducted.

Preliminary Interviews

In order to include the experience gained so far in practice in the model development, six expert interviews with insurance companies were carried out. This approach was necessary to gather information, as the research topic is still in its infancy and literature is limited. The qualitative design of the interviews involves the use of pre-formulated questions, which allow improvisation for emerging topics during the conversation where necessary. Interviewees were mostly comprised of managers from different sectors ranging from health care and contract management to mobile device program managers and digital risk managers of large private and statutory health insurances. The main objective of the interviews was to gain an insight into the company view and opinion regarding the use of wearable technology for PAYL services and to obtain an overview of possible challenges and success factors. Overall, about 33

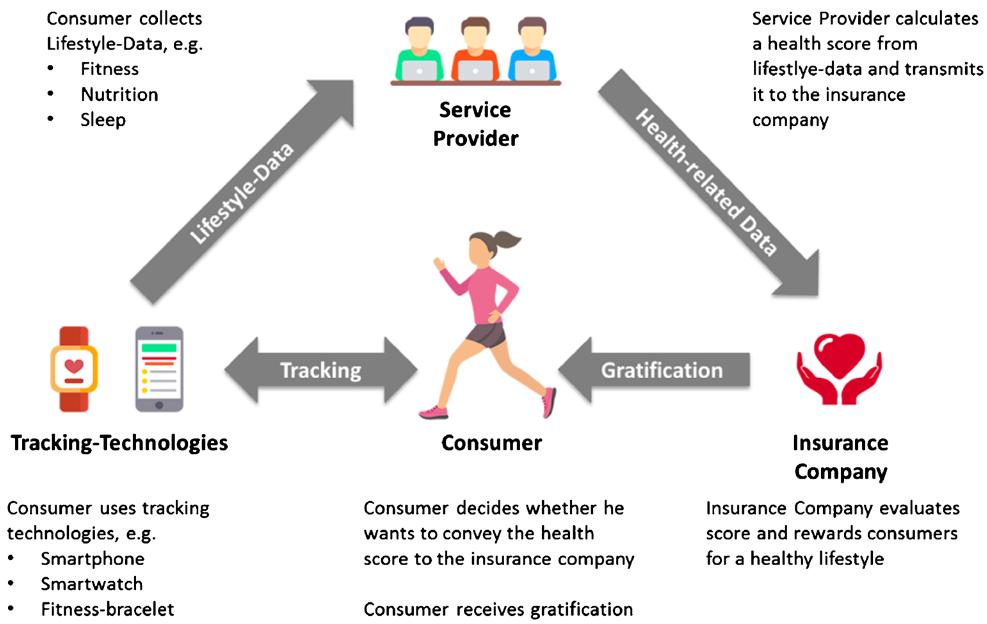

Fig. 1 PAYL service process

insurance companies were contacted. Five of the six arranged interviews were conducted by telephone during May and June 2016, while the remaining one was carried out in person. All interviews were recorded after obtaining the consent of the expert in question. The duration of the interviews was between 16 min to 35 min. The recorded interviews were used for a full transcription. In order to evaluate the interviews, the data was interpreted according to Mayring's (2010) content analysis. In this approach, the analysis proceeds according to specific rules. The structuring content analysis was applied using deductive and inductive categories and anchor samples were subsequently paraphrased and generalized using MAXQDA. For key categories, the description and encoding rules are summarized and no further rules are required to limit the encoding. As Success factors represent the most important category in this research study, the interviews were first searched for these and the findings from coding were then evaluated and compared with the relevant literature.

Overlapping and predominant factors were chosen and tested in the model to explain the success of wearable technologies for insurance companies namely: information sensitivity (IS), regulatory expectations (RE), privacy concerns (PC), perceived benefits (PB), perceived value (PV), perceived usefulness (PU), perceived enjoyment (PE), effort expectancy (EE) and functional congruence (FC).

Conceptual Basis and Hypothesis Generation

According to the conducted expert interviews and based on the comprehensive literature review predominate factors affecting the use of wearables for PAYL services were extracted. One of the most important key drivers is perceived value. In addition, experts named privacy concerns as the biggest obstacle among German insurants. Culnan and Armstrong (1999) found that people with greater privacy concerns were less willing to collect personal data unless explicitly stated that their personal data were handled with care. The authors were the first to call this theory the "privacy calculus" (p. 106). PCT has thus been chosen as the main framework because individuals compare perceived privacy risks (PPR) with anticipated benefits. The performed risk-benefit analysis yields the perceived value, which is a more suitable antecedent of intention to use wearable technology (Yang et al. 2016). Furthermore, PCT explains drivers and barriers of information disclosure when insurants are requested to provide personal information to insurance companies when participating in a wearable supported bonus program (Li et al. 2016). Hence, PCT extended with PV is believed to represent the given scenario. Prior studies prove empirical support for both the PCT (e.g. Li et al. 2016, Dinev and Hart 2006) as well as the effects of perceived benefits and perceived risks on perceived value in m-Internet and wearable context (e.g. Kim et al. 2007, Yang et al. 2016).

Proposed by Zeithaml (1988), PV represents the consumer's overall assessment of the utility of a product. Only if benefits outweigh privacy risks, are individuals more likely to use wearable technology in an insurance context. PV was proven to positively affect behavioral intention, as also shown by Chen (2008), Kim et al. (2007) and Boontarig et al. (2012). Actual behavior is indirectly influenced by attitude via behavioral intention, which in turn has a direct long-term effect on attitude (e.g. Trommsdorff 2004). In a theoretical context, several authors, e.g. Anderson and Agarwal (2010) and Siponen and Vance (2010) argue that the relationship between behavioral intention and actual behavior is based on the Theory of Planned Behavior (Ajzen 1991) and the Theory of Reasoned Action (Fishbein 1979). This conjecture has since been proven empirically by Anderson and Agarwal (2010). A number of studies emphasize the relationship between actual behavior and behavioral intention (for example Limayem and Hirt 2003, Kim 2005, and Tao 2009). We thus follow the generally accepted view that intention to use (referring to an attitude) is not a substitute but a determinant and hence a predictor of behavior such as the decision to adopt PAYL services using wearable technologies.

This study thus proposes the following hypotheses:

- **Hypothesis 1:** Perceived value is positively associated with intention to use wearables for PAYL services.

Consistent with other studies, PPR is understood to be the expectation of losses associated with certain actions, in particular the extent to which a person believes that using a wearable device for PAYL services has negative consequences concerning one's privacy (Malhotra et al. 2004, Xu et al. 2008). As wearables collect and store sensitive health information users might willingly or unwillingly share their data with third parties such as device manufacturers and app providers (e.g. Google and Apple Health App) in addition to their insurance company. While users often cannot control what information is transmitted to what entity and how it is used, individuals perceive the product as less valuable, if privacy risks outweigh their perception (Ernst and Ernst 2016).

- **Hypothesis 2:** The perceived privacy risk by individuals is negatively associated with perceived value.

Perceived benefits are jointly formed from intrinsic and extrinsic factors. Whereas intrinsic motivation yields from individual fun and enjoyment performing the activity per se, extrinsic motivation has a functional and utilitarian character (Kim et al. 2007, Yang et al. 2016, Rogers 1995). Intrinsic and extrinsic factors motivate people to use wearable technology. According to an answer from an interview partner, insurants can benefit from these products while strengthening their self-management with regard of their healthcare. They hence become motivated to follow a healthier and more active lifestyle. Based on the foregoing, the following hypothesis is formulated:

- **Hypothesis 3:** The benefit perceived by individuals is positively associated with perceived value.

Whereas specific antecedents of privacy calculus may vary depending on different contexts, e.g. monetary and technical sacrifices (Kim et al. 2007, Yang et al. 2016), this paper focuses on the factors information sensitivity, regulatory expectations and MUIPC for predicting PPR. Wearable devices used for PAYL services involve sensitive health information (Li et al. 2016) and experts confirm that these health data comprise the product core. Information sensitivity (IS) describes the degree of discomfort perceived by an individual when health information is disclosed to an external entity, in this case the insurance company or a third-party provider that processes the data (Li et al. 2016, Dinev et al. 2013). Furthermore, Li et al. (2016) and Dinev et al. (2013) acknowledged that the type of information collected and used by organizations affects the level of an individual's perceived privacy concerns. This study hence suggests that risk perceptions increase when the requested or collected information is regarded as sensitive.

- **Hypothesis 4:** The perceived information sensitivity of individuals is positively associated with their perceived privacy risk.

Regarding privacy risks, regulatory expectations are required as a determinant for investigating the perceived privacy risk of an individual (Dinev et al. 2013, Li et al. 2016, Xu et al. 2009). According to the interviewed experts, the drafting of rules and laws is an important premise in this respect. They stress the need for legislative support to provide further guidance. At present, the laws regarding wearables are still unclear. As suggested by Dinev et al. (2013), we argue that insurants who expect strict privacy regulations are more likely to be concerned about the risk of their personal information disclosure. Hence, we hypothesize that:

- **Hypothesis 5:** The regulatory expectations perceived by individuals are positively associated with their perceived privacy risk.

MUIPC is chosen as a relevant predictor for PPR in order to highlight the importance of the existing mobile privacy concerns that arise using wearable technology (Xu et al. 2012), especially for PAYL services. However, this is a direct added relationship, which has not been tested before. The MUIPC model is based on the "concerns for information privacy" (CFIP) model by Smith et al. (1996). The CFIP model has been widely applied in various contexts, including healthcare (Angst and Agarwal 2009). Xu et al. (2012) developed a new model, which focuses on the perceived privacy concerns of mobile technology users. In this study, MUIPC is modelled using the three dimensions "secondary use of information" (SUI), "errors" (ER) (Smith et al. 1996, Stewart and Segars 2002) and "perceived intrusion" (INT) (Xu et al. 2012). SUI describes the situation in which information collected from an individual is not only used for a specific purpose but also for another without the user's consent. ER refers to an individual's believe that organizations are not taking enough steps to reduce problems and that incorrect data might be present. INT defines incidents that encroach on the everyday lives of individuals, disrupt their daily routine and activities and often make them feel uncomfortable. Hence, it is reasonable to hypothesize that MUIPC directly influences perceived privacy risks.

- **Hypothesis 6:** The privacy concerns of mobile users are positively associated with their perceived privacy risks.

PU (Perceived Usefulness) is defined as the degree to which an individual believes that using wearable technology would be beneficial and enhance the achievement of a goal associated with such devices (Pfeiffer et al. 2016). PU has strong empirical support as an important predictor of technology adoption (e.g. Davis 1989; Venkatesh 2000, Venkatesh et al. 2012, Kim and Shin 2015) and is often referred to as performance expectancy in other studies (Yang et al. 2016, Kim et al. 2007, Gao et al. 2015). Users of wearable technology can improve their health management by making individual healthcare plans and reduce health related threats by participating in a preventive healthcare measurement scheme such as a PAYL service. According to the interviewed experts, participants can gain a better understanding of their health and fitness behavior while collecting and monitoring their physical condition and can also improve their exercise routine. When insurants believe that using wearable devices can enable them to increase these kinds of healthcare benefits, they are more likely to perceive it as being beneficial. This study thus proposes:

- **Hypothesis 7:** Perceived usefulness will positively affect an individual's perceived benefit.

PE (Perceived Enjoyment) refers to the experienced pleasure and joy from the use of wearable technology while getting involved personally apart from any performance consequence that may be anticipated (Kim et al. 2007). Ernst and Ernst (2016) suggest that the use of smartwatches is influenced directly by hedonic motivation, an original UTAUT 2 construct, akin to PE. This finding supports the experts' suggestion to emphasize gamification, which in turn refers to PE, because these devices support the gamification trend lived by individuals wanting to compete with each other or improve their performance. The experts assume that when using wearables, their insurants have a goal in mind such as health tracking or weight loss. Therefore, people buy and use wearables that they can actually work with. Furthermore, individuals pay more attention to the enjoyment of the products since wearable devices send the message of an enjoyable experience and not merely that of a healthcare device (Gao et al. 2015). This study hence hypothesizes that:

- **Hypothesis 8:** Perceived enjoyment positively affects an individual's perceived benefits.

EE (Effort Expectancy) is widely known as "the degree of ease associated with a consumer's use of technology" (Venkatesh et al. 2012, p.159). Compared with other emerging technologies, the use of wearable devices is generally more complicated, as they require users to continuously wear them and use other devices such as smartphones and apps at the same time. Gao et al. (2015) found that EE positively affects the intention of consumers to adopt healthcare wearable devices. The interviewed experts also support this view. From the perspective of insurants wearable supported prevention measures must be easy to use, comfortable and intuitive. If an insurant perceives this, they are more likely to perceive a benefit and consequently perceive a value. Hence, this study proposes that EE is a relevant determinant for predicting perceived benefits:

- **Hypothesis 9:** The effort expectancy positively affects an individual's perceived benefits.

FC represents the overall quality of wearable devices, in particular the perceived suitability of a product to meet functional as well as basic product-related needs (Li et al. 2016). It also refers to a quality characteristic that can be observed or experienced by consumers before the product is bought (Gao et al. 2015). If insurants observe higher product quality, they are more likely to use wearable device in PAYL services (Gao et al. 2015). Pfeiffer et al. (2016) suggest that design (perceived aesthetics) has no effect on the intention to use wearable tracking technology. Albeit, experts stress the importance of proper functional attributes and design, and are convinced that insurants are more likely to perceive a benefit due to e.g. longer battery life, good design or high sensor accuracy. Therefore, we hypothesize that:

- **Hypothesis 10:** Functional congruence positively affects an individual's perceived benefits.

Research Design and Methodology

Survey Design

Quantitative empirical methods, in particular surveys, are considered as suitable research approaches in order to obtain results with high generalizability (e.g. Lee and Baskerville 2003). We thus chose survey methodology to collect empirical data and multivariate analysis methods to test the revised model statistically. Empirical data for this study were collected via a Lime survey between August 2016 and January 2017 from three social network groups associated with healthcare wearable devices and two forums on the topics wearables tech, fitness and smartwatches. The subjects could easily participate by using the URL provided in the posting. Furthermore, the questionnaire was distributed via E-mail. At the beginning of the survey, the participants were shown the figure with the PAYL service process from the theoretical background section and an explanation of the use of wearable technology for PAYL services outlining the possible benefits, in order to guarantee that the participants were sufficiently informed to answer the questions posed. The role of the service provider, which transmits a score to the insurance company using the incoming data from the insurants, was explained to the participants at the beginning of the questionnaire. Although it was made clear to the participants that the contract is concluded only with the insurance company, it was pointed out that the entire process, including an evaluation by the service provider, should be considered when answering the questions.

The questionnaire is composed of two parts. The first part retrieves the attitude of the respondents to each item (Table 3) while the second part requests the respondents' demographic information. In order to ensure content validity, all items were adapted from previous research studies and modified in wording to fit into a wearable technology context. In addition, a content validity expert panel comprised of eight doctoral and faculty students skilled in quantitative research methods and analysis, performed a content validity analysis for the instrument scales according to Johnston and Warkentin (2010). In the final study, a total of 458 subjects participated. 353 of the latter submitted usable data (77%), see Table 4. Due to the fact that 105 questionnaires were not filled out completely, we had to drop them out. Our sample is expected to be representative for investing PAYL services using wearable technology.

Measurement and Instrumentation

All items were measured on a five-point Likert scale with anchors ranging from 1 "strongly disagree" to 5 "strongly agree". In total, the 40 measurement items describe 11 constructs. While 10 constructs were operationalized as first-order factors, MUIPC is represented as a second-order factor with three first-order dimensions: ER, SUE and INT. Multidimensional constructs, such as second-order constructs, permit the compilation of complex concepts by way of comparatively simple abstractions (Polites et al. 2012). A second-order factor model represents the structure of MUIPC more sparingly than a first-order factor model (Xu et al. 2012). For this reason, we conceptualize MUIPC as a second-order construct. In order to prepare for the empirical validation of the research model, we relied, as far as available, on established and proven measurement scales to increase the validity. The items for information sensitivity, regulatory expectations, perceived privacy risk and perceived benefits are based on work by Li et al. (2016) and Dinev et al. (2013). The constructs secondary use of information, errors and perceived intrusion were measured by items adapted from Stewart and Segars (2002), Xu et al. (2008) and Xu et al. (2012). The scales for measuring perceived usefulness, perceived enjoyment, functional congruence and effort expectancy were adapted from Gao et al. (2015), Venkatesh et al. (2012) and Hew et al. (2015) while perceived value was derived from Kim et al. (2007). For measuring intention to use, we adapted a scale reported by Gu et al. (2015).

Data Analysis and Results

This section describes the data analysis and results, including, e.g., a description of instrument validity and an internal validity test. The research model and its results are presented and discussed in the next section (see Fig. 2). Empirical data were analyzed by means of structural equation modeling (SEM) to test the causal-effect relations among the latent constructs. SEM integrates the measurements and the structural model (hypothesized causal paths) into a concurrent evaluation (Gefen et al. 2011). According to Degirmenci et al. 2013, SEM thus offers researchers the flexibility to model a relationship among criterion variables and multiple predictors, such as model errors in measurements for observed variables, to design unobservable latent variables, and to statistically test a priori theoretical and measurement assumptions against empirical data (Chin 1998). Researchers should be cautious, however, when interpreting the results regarding causal relationships. SmartPLS (partial least squares) Version 2.0.M3 was used for model testing and measurement validation. PLS is a variance analytical SEM technique that utilizes a component-based approach to estimation. It is advantageous if the research model has a variety of indicators, is relatively complex, and the measures are not well-established (Fornell and Bookstein 1982). PLS does not impose a normality requirement on the data and can handle both reflective and formative constructs (Sun 2012; Wetzels et al. 2009). We captured the entire domain of the constructs and decided at the theoretical level whether the constructs in the underlying research field were reflective, formative, or a combination to ensure content validity. After examining the relationship between each indicator and the construct, we determined the overall constructs in the research model to be reflective. We conceptualize our research model to be reflective, due to the direction of the causality, the interchangeability of the indicators, the covariation among the indicators, and the nomological net of the constructs, which should not differ.

Before the overall model was analyzed, item reliability, construct validity, composite reliability, and convergent and discriminant validity were examined. To ensure the reliability of the items, the loadings of each item were measured for their respective underlying construct. Item loadings are recommended to be above at least 0.6 and ideally above the threshold of 0.707, indicating that at least 50% of the variance is shared with the respective construct (Chin 1998). The item reliability analysis shows that all items ranged from a minimum of 0.650 to a maximum of 0.952, demonstrating that all items are reliable for further analysis. The t-values ranged from 36.467 to 109.855, which indicates significance for all item loadings at $p < 0.001$. Furthermore, the construct validity was checked by testing for cross-loadings. In

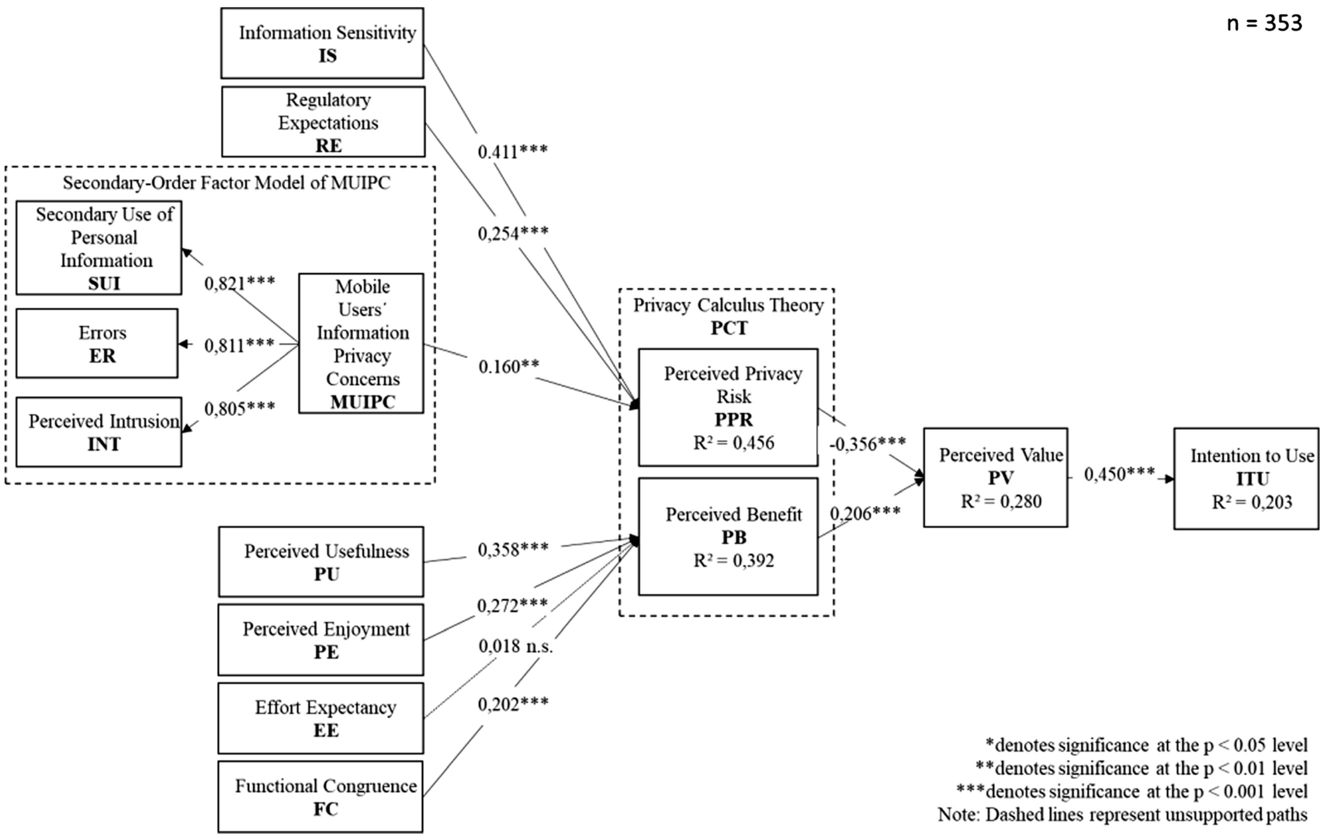

Fig. 2 PLS Results

this study, no cross-loadings were identified, which means that all indicators load on those constructs on which they were intended to load (Straub et al. 2004). The discriminant and convergent validities were assessed by the average variance extracted (AVE). Firstly, "discriminant validity can be established if item-to-construct correlations are higher with each other than with other construct measures and their composite values" (Johnston and Warkentin 2010, p. 557). Here, the condition for discriminant validity is met. AVE estimates the overall amount of variation that a latent construct is able to explain in the manifest or observed variables to which it is theoretically related. In this model, the AVE values for all constructs are higher than the recommended threshold value of 0.50 (Bhattacherjee and Premkumar 2004). The fact that the square root of the AVE for each construct exceeds its correlation with any other latent variable indicates that each construct shares more variance with its indicators than it shares with the other constructs (see Table 5). Additionally, construct cross-loadings show that the loads of each measure are higher (shares more variance) on its own construct than on any of the other constructs (see Table 6).

According to Degirmenci et al. 2013, we measure the internal consistency, which is similar to Cronbach's alpha, with the composite reliability or internal consistency reliability (ICR). As the ICR values were found to range from 0.7551 to 0.9473, which is above the threshold values of 0.7 (Diamantopoulos et al. 2008), the internal consistency reliability for all constructs is given. In overall terms, the evidence of reliability, convergent validity, and discriminant validity indicates that the measurement model was appropriate for testing the structural model in a subsequent stage (Table 1).

After testing the measurement model, the structural model was tested on grounds of heuristic criteria. To receive valid results of the PLS path modelling analysis, the bootstrapping resampling procedure was used with 1000 resamples to obtain estimates of standard errors for testing the statistical significance of a path coefficient using the t-test. In this way, the analysis produced estimates of both the explained variance and path coefficients.

Relating to the whole sample, SEM revealed that nine out of ten proposed hypotheses could be confirmed, as shown in the overall findings in Table 2.

As indicated in Fig. 2, the model explains approximately 23% of the overall variance. The explanatory power of 28% of PV are the paths from the constructs of PPR and PB. The R^2 of the dependent variable PPR is at 46%, while R^2 of PB is at an explanatory power of 39%.

Discussion, Recommendations, and Limitations

The main scope of this study has been to analyze the adoption of PAYL services using wearable technology. The focus here was to perform a risk-benefit-analysis and compare perceived privacy

Table 1 Validity and Reliability Criteria

Constructs	Indicators	Std. loading	t-value	Average Variance Extracted (AVE) AVE(i) ≥ 0.5	Composite Reliability (ICR) ($p \geq 0.7$)
IS	IS 1–3	0.841–0.919	45.932–59.018	0.7657	0.9073
RE	RE 1–3	0.791–0.873	78.456–83.960	0.7163	0.8832
SUI	SUI 1–3	0.841–0.885	84.627–109.855	0.7392	0.8948
ER	ER 1–2	0.650–0.790	65.804–74.937	0.5150	0.7599
INT	INT 1–3	0.684–0.728	57.638–65.022	0.5070	0.7551
PU	PU1–3	0.69–0.848	49.135–61.467	0.6280	0.8340
PE	PE 1–3	0.788–0.912	64.290–71.428	0.6992	0.8741
EE	EE 1–3	0.767–0.869	70.587–76.835	0.6447	0.8444
FC	FC 1–3	0.673–0.779	71.696–88.372	0.5494	0.7846
PPR	PPR 1–3	0.909–0.952	54.360–55.428	0.8569	0.9473
PB	PB 1–3	0.899–0.903	53.155–60.918	0.8107	0.9278
PV	PV 1–4	0.738–0.934	50.007–56.681	0.5506	0.8913
ITU	ITU 1–2	0.928–0.928	36.467–39.449	0.8628	0.9263

IS Information Sensitivity, *RE* Regulatory Expectancy, *SUI* Secondary Use of Information, *ER* Errors, *INT* Perceived Intrusion, *PU* Perceived Usefulness, *PE* Perceived Enjoyment, *EE* Efforl Expectancy, *FC* Functional Congruence, *PPR* Perceived Privacy Risk, *PB* Perceived Benefit, *PV* Price Value, *ITU* Intention to Use

risk and perceived benefit from a customer perspective. Based on the latter, this study was driven by one general research question: How do perceived privacy risk and perceived benefit influence the adoption of Pay-As-You-Live services using wearable technologies? In an attempt to answer this question, a research model was developed in this study with antecedents of perceived privacy risk and perceived benefit to determine perceived value and the intention to use wearable technology for PAYL services. Although other studies suggest that intention to use is a determinant and predictor of behavior, it should be noted that this study measures attitudes and no actual behavior. Further studies are necessary to measure actual behavior and obtain clear evidence of convergent validity. The attitudes in this research form anticipation and no reflection of experiences already made. This can lead to correlation among individual latent variables. For example, the latent variables PE, PU, and PV have an increased correlation as it can be seen in Table 5. These variables would have to be better differentiated with the help of a behavioral focused research. Furthermore, it should be noticed that not every single participant has experience in wearable technology usage so far. It was inevitable to give them the necessary information towards potential benefits and risks. In accordance with this procedure, we do not believe that results might differ if the technology is more widespread and the customer is more experienced in the use of wearables. The most important finding is that the path coefficient of perceived privacy risk is almost twice as high as that of perceived benefit. Furthermore, this paper demonstrates that the information privacy concerns of mobile users has an influence on the determination of perceived privacy risk. Figure 2 shows the estimates of the path coefficients, significance levels and R^2 values of research hypotheses.

The results of our study yield an R^2 value of 0.203 for intention to use. Thus, 20% of the variance of intention to use is explained by perceived value. Therefore, we recommend considering the construct of perceived value along with further constructs such as perceived usefulness and perceived

Table 2 Overview of Findings

Hypothesis (with direction)	Path coefficient (ß)	t-value	*p*-value	Support
H1: PV → ITU (+)	0.450***	7.427	p < 0.001	Supported
H2: PPR → PV (−)	0.386***	6.446	p < 0.001	Supported
H3: PB → PV (+)	0.206***	3.279	p < 0.001	Supported
H4: IS → PPR (+)	0.411***	6.431	p < 0.001	Supported
H5: RE → PPR (+)	0.254***	4.543	p < 0.001	Supported
H6: MUIPC → PPR (+)	0.160***	2.563	*p* < 0.05	Supported
H7: PU → PB (+)	0.358***	5.627	p < 0.001	Supported
H8: PE → PB (+)	0.272***	4.097	p < 0.001	Supported
H9: EE → PB (+)	0.018	0,305	*p* > 0.10	Not Supported
H10: FC → PB (+)	0.202**	3.670	p < 0.001	Supported

ease of use (Davis 1989), attitude towards behavior, subjective norm and perceived behavioral control (Ajzen 1991), and technology readiness (Parasuraman and Colby 2015). Thus, a comprehension of intention to use PAYL services could be further enhanced. In addition, the sample included in this study is distorted towards younger participants and more than 75% of our participants were younger than 45. Nevertheless, we believe that our study makes an important contribution to the field of wearable technology and PAYL services. Presumably, younger people use wearables as it is a new trend. Comparing the coefficients and significance levels, the results show that the impact of perceived privacy risk is almost twice as much as that of perceived benefit. Privacy concerns thus have a much greater impact on perceived value and therefore on the intention to use PAYL services than perceived benefit. Even if insurants recognize that wearables are beneficial, they may still not find it valuable unless they perceive the privacy risks to be less than the benefits they receive.

In our research, it was found that **information sensitivity** has the greatest impact on perceived privacy risk for customers. IS describes the degree of personally perceived discomfort when health information is disclosed to an external service provider. Many of the respondents don't feel comfortable with the type of information wearables collect from them. Furthermore, they feel that the gathered data are very sensitive and that it is too risky to disclose their personal health information to insurance companies. Additionally, respondents using wearable technology believe that there would be a high potential for loss and too much uncertainty disclosing health information to insurance companies. Collecting sensitive health information could, however, be beneficial in certain situations according to three of the interviewed experts. The collected health data can be used to strengthen the self-management and health knowledge of an individual, and potentially avoid unnecessary doctor appointments on the grounds of being able to understand one's health information better. From the viewpoint of the insurance companies, the collected information offers them a great opportunity to provide individualized services and products regarding e.g. disease management or movement and nutrition services to their insurants. As a limitation, however, it must also be seen that all expert interviews were made in the insurance companies and therefore reflect the view of the insurers not of their customers.

Furthermore, the **information privacy concerns** of **mobile users** have been successfully proven to affect their perceived privacy risk. This direct relationship has never been tested before. In particular, insurance companies should reduce uncertainty regarding the secondary use of information. They have to ensure that the collected data are only used to reward the insurant and are not used or sold for other purposes. Here, the benefit must be clearly communicated to the customer, while at the same time, the fear of data misuse or loss must be dispelled. For example, by offering different levels of privacy in an independent privacy cloud. Insurance companies must therefore be more transparent about what exactly happens to a customer's data at all times. Furthermore, respondents have concerns about possible errors in the calculation of scores or in the transmission of their sensitive health data. Excellent data management and data governance need to be thought through when designing healthcare products, which should assure data security and provide privacy-related orientation. Beyond this, insurance companies need to protect themselves against potential cyber-attacks and data abuse not only through apps and wearable devices but also by third parties. Therefore, there are considerations to leave the tracking and evaluation of the health and behavioral profiles to an independent digital platform. In overall terms, it is of great importance to reduce concerns regarding perceived privacy risk in order to increase the perceived benefit of costumers.

Additionally, **regulatory expectations** have been verified to positively influence perceived privacy risk. Respondents believe that the law should protect them from the misuse of personal health data and regulate the way in which insurance companies collect, use, and protect private information. Since data transmission is defined by the wearable manufacturer or app service provider, customers tend to feel insecure using wearable devices (McAdams et al. 2011, Ching and Singh 2016). Maybe the success of services such as PAYL can be ensured if laws regulate the boundaries of data deployment and data transmission. This process should be regulated in a consistent manner.

Focusing on the factor **perceived benefit**, it is no surprise to find that **perceived usefulness** is one of the most influencing factors, which is in keeping with past findings reported in the literature. The utilitarian purpose seems to score off any other proposed antecedents. However, cultural differences and the perceived prestige of insurance companies may also have an impact on the decision of an individual to use PAYL services. These factors were not considered in this study.

The second largest factor found to influence perceived benefit in this study is **perceived enjoyment** / hedonic motivation. The individualization and objectivization of one's own life through the health data recorded by wearables imparts a feeling of gaining control over our lives. This provides the customer with a new, objective and factual assessment that appears rational. The impression of control is enormously important for one's own happiness and thus explains the hedonistic context identified in this study. For this reason, it is particularly important for insurance companies not only to create a purely functional insurance service, but also to increase the joy and pleasure of its use. Fitbit, with the world's largest market share for wearables, provides good examples of a positive influence on the factor of hedonistic motivation. In their application, which can be connected to the wearable via Bluetooth, it is possible to share training tasks and results with other users, receive notifications from friends and challenge them to competitions. The implementation of a gamification factor, i.e. the application of game-specific elements such as experience points, high scores, progress bars and ranking lists, can increase the motivation and the joy of the user and thus contribute to the adoption of smart PAYL services. With regard to the gamification factor, it is especially important to keep the service dynamic and interesting for young users. With the help of certain service-specific features, it might be possible to increase the perceived enjoyment, which in turn could have a positive effect on the intention to use.

Functional congruence has a significant positive effect on an individual's perceived benefits. Broadly speaking, the functional quality of wearables is a necessity for proper (data) processing. Wearable devices do not only have to be high quality products ensuring long battery life and sensor accuracy but should also be comfortable and fashionable at the same time, so that they incorporate seamlessly into people's wardrobes and become an extension of an individual's body for supporting individual benefits. In order to guarantee a smart service, companies need to focus on the compatibility between analysis-apps, smartphones and the data transmission process from one device to another. As things are at present, insurants are limited to specific wearable manufacturers (e.g. Fitbit) and restricted in their choices. Nevertheless, the wearable market is characterized by a large differentiation between various devices, all of which have different benefits and drawbacks that should be considered. Moreover, there are other relevant factors not considered in this study such as service providers or the pharma industry.

Effort expectancy does not significantly influence perceived benefits. An explanation could be that the survey took place at a time where wearable supported insurance services like PAYL are not widespread in Germany, which is why participants most likely do not have experience with those services.

From a theoretic point of view, **perceived value** has been shown a clear predictor of individual's intention to use wearable devices for PAYL services. This finding supports related theories and strengthens the common believe that perceived value plays an important part in individual's decision of accepting new products and services (Yang et al. 2016). Consequently, customers need to perceive a value from the wearable supported services, so that those can successfully ensure individual's interest and intention to use. This might be possible, once the use of wearable devices fosters benefits such as providing valuable health information insurants might not have otherwise and reward them for active behavior or by advising potential fitting preventive measures. Insurance companies also gain a benefit proposing those products, given that accurate processes of coordination of planning and smart-IT solutions are present through the whole project. Only then, they can deal with the huge amount of data accurately, in particular in terms of data quality and appropriate management. The health and risk profiles are very valuable for insurers and their service providers in the long term. Tracking tariffs offer the opportunity to attract new customers with good risk characteristics and at the same time encourage existing customers to rethink their risk behaviors. Moreover, new insights into the relationship between lifestyle and disease are also conceivable by analyzing the collected data.

Conclusions and Further Research

This study advances the understanding of pay-as-you-live services using wearable technology. Based on the results of this research, it may be concluded that the risk-benefit analysis yields a perceived value, which is a significant determinant of an individual's intention to use wearable devices in PAYL services. An important finding from the costumer perspective is that the influence of perceived privacy risk on perceived value is almost twice as high as that of perceived benefit. Therefore, a prerequisite for the successful implementation of PAYL services on the market is that insurance companies, service providers and manufacturers of wearables should primarily work together and offer solutions for more data security and data protection before working on further features of the devices. Insurance companies should first reduce their customers' concerns about personal data and their transmission before paying attention to gamification factors so as to increase perceived enjoyment or to functional congruence when selecting the appropriate wearables. At the present time, insurants are awaiting further developments on the insurance market and the solution of privacy-related concerns. Previous research indicates that people are willing to participate in these programs as long as they perceive benefits. Therefore, insurance companies do not only have to collaborate with wearable manufactures to ensure improved data security and transmission but also to enhance transparency regarding the use of data and the prevention of possible data theft and manipulation by third parties. More importantly, insurance companies will need to focus on the right balance of technology, data privacy, wearable functionality, usefulness and a sustainable business model in order to be successful. Individuals might not be willing to invest time, effort or money in wearable healthcare devices unless the certainty of their benefits is guaranteed.

Upcoming studies should investigate what other benefits could enhance the perceived value such as monetary compensation (discounts, coupons, and rebates) as an additional benefit factor and should also attempt to increase the variance explained. In addition, the interviewed experts suggested that the perceived prestige of insurance companies as well as trust might also be important points of consideration. Lastly, it would be informative to investigate the proposed model with moderated variables such as prior wearable experience and insurance type as well as to investigate differences between age groups, considering that the opinions of experts diverged on these factors. The interviews revealed that wearable supported bonus programs would better suit private insurance offers. At present, however, statutory insurance companies launch these services much earlier on the market. These fine distinctions could provide a further refined picture.

Appendix

Table 3 Survey Instrument

Construct	Indicators	Items
Information Sensitivity (IS)	IS1	I do not feel comfortable with the type of health information wearable technology collects from me.
	IS2	I feel wearable technology gather highly personal health information about me.
	IS3	The health information I should provide to wearable technology is very sensitive to me.
Regulatory Expectations (RE)	RE1	I believe that the law should protect me from the misuse of my personal health data by insurance companies.
	RE2	I believe that the law should govern and interpret the practice of how insurance companies collect, use, and protect my private information.
	RE3	I believe that the law should be able to address violation of the information I provided to insurance companies.
Perceived Privacy Risk (PPR)	PPR1	It would be risky to disclose my personal health information to insurance companies.
	PPR2	There would be high potential for loss associated with disclosing my personal health information to insurance companies using wearable technology.
	PPR3	There would be too much uncertainty associated with giving my personal health information to insurance companies using wearable technology.
Perceived Benefits (PB)	PB1	Using wearable technology would improve my access to my health information.
	PB2	Using wearable technology would improve my ability to manage my health.
	PB3	Using wearable technology would improve the quality of my healthcare.
Functional Congruence (FC)	FC1	Wearable technology is expected to be comfortable.
	FC2	Wearable technology is expected to be priced appropriately considering their quality.
	FC3	Wearable technology is expected to be fashionable.
Effort Expectancy (EE)	EE1	Learning how to use wearable technology is easy for me.
	EE2	I find wearable technology easy to use.
	EE3	It is easy for me to become skilful at using wearable technology.
Perceived Usefulness (PU)	PU1	I find wearable technology useful in my daily life.
	PU2	Using wearable technology helps accomplish things more quickly.
	PU3	Using wearable technology improves the quality of my daily healthcare seeking.
Perceived Enjoyment (PE)	PE1	Using wearable technology is fun.
	PE2	Using wearable technology is enjoyable.
	PE3	Using wearable technology is entertaining.

Table 3 (continued)

Construct	Indicators	Items
Perceived Value (PV)	PV1	Compared to the price I need to pay; the use of wearable technology offers value for money.
	PV2	Compared to the effort I need to put in, the use of wearable technology is beneficial to me.
	PV3	Compared to the time I need to spend; the use of wearable technology is worthwhile to me.
	PV4	Overall, the use of wearable technology delivers me good value.
Secondary Use of Personal Information (SUI)	SUE1	Insurance companies should not use personal information for any purposes unless it has been authorized by the individuals who provided the information.
	SUE2	When people give personal information to an insurance company for some reason, the company should never use the information for any other purpose.
	SUE3	Insurance companies should never sell the personal information in their computer databases to other companies.
Errors (ER)	ER1	All the personal information in computer databases should be double-checked for accuracy—no matter how much this costs.
	ER2	Insurance companies should have better procedures to correct errors in personal information.
	ER3	Insurance companies should devote more time and effort to verifying the accuracy of the personal information in their databases.
Perceived Intrusion (INT)	INT1	I feel that as a result of me using these insurance products, others know about me more than I am comfortable with.
	INT2	I believe that as a result of me using these insurance products, the information about me that I consider private is now more readily available to others than I would want to.
	INT3	I feel that as a result of me using these insurance products, my privacy has been invaded by the others that collect all the data about me.
Intention to Use (ITU)	ITU1	I intent to use wearable supported services provided by insurance companies in the future.
	ITU2	I am very likely to provide the insurance companies with the information it needs to better serve my needs.

Table 4 Respondent Demographics

Characteristics (n = 353)		Frequency	Percentage
Gender	Female	172	48.72
	Male	181	51.12
Age	18 or under	29	8.22
	19–25	104	29.46
	26–35	96	27.20
	36–45	62	17.56
	46–60	49	13.88
	60 or older	13	3.68
Insurance type	Statutory Health Insurance	291	82.44
	Private Health Insurance	62	17.56
Wearable experience	Yes	134	37.96
	No	219	62.04

Table 5 Correlations of the Constructs and Square Root of AVE

	EE	ER	FC	INT	IS	ITU	PB	PE	PPR	PU	PV	RE	SUE
EE	**0.899**	0	0	0	0	0	0	0	0	0	0	0	0
ER	−0.0426	**0.8177**	0	0	0	0	0	0	0	0	0	0	0
FC	0.4073	0.1638	**0.822**	0	0	0	0	0	0	0	0	0	0
INT	−0.2755	0.236	−0.016	**0.8992**	0	0	0	0	0	0	0	0	0
IS	−0.0685	0.1147	0.2672	0.6051	**0.852**	0	0	0	0	0	0	0	0
ITU	0.2755	−0.1704	0.0027	−0.4622	−0.4704	**0.9288**	0	0	0	0	0	0	0
PB	0.2633	−0.0294	0.2951	−0.2563	−0.2995	0.3641	**0.892**	0	0	0	0	0	0
PE	0.5412	−0.1532	0.2242	−0.2562	−0.1637	0.4569	0.3861	**0.844**	0	0	0	0	0
PPR	−0.3347	0.2007	−0.1006	0.7207	0.6137	−0.4652	−0.338	−0.2991	**0.919**	0	0	0	0
PU	0.3389	0.0911	0.1647	−0.1377	−0.1928	0.4734	0.5561	0.553	−0.2169	**0.852**	0	0	0
PV	0.4398	−0.118	0.0447	−0.3561	−0.3189	0.5796	0.3192	0.675	−0.3622	0.5398	**0.84**	0	0
RE	−0.0858	0.3226	0.255	0.2663	0.3742	−0.4281	−0.0327	−0.2413	0.337	−0.2282	−0.3729	**0.777**	0
SUE	0.1815	0.2924	0.3139	0.2967	0.2829	−0.2059	−0.0888	−0.127	0.1587	−0.3273	−0.265	0.4405	**0.819**

Table 6 Construct Cross-Loadings

	EE	ER	FC	INT	IS	ITU	PB	PE	PPR	PU	PV	RE	SUE
EE1	**0.8781**	−0.0135	0.3654	−0.1923	−0.0026	0.2693	0.1715	0.4283	−0.2648	0.2603	0.3518	−0.0445	0.2497
EE2	**0.8997**	−0.1337	0.3466	−0.2986	−0.1321	0.2555	0.2101	0.5353	−0.3692	0.2915	0.4557	−0.0969	0.1445
EE3	**0.9206**	0.0147	0.3846	−0.2464	−0.0463	0.2324	0.2961	0.4912	−0.2768	0.343	0.3822	−0.0828	0.1281
ER1	−0.0462	**0.9993**	0.1611	0.2412	0.1183	−0.1788	−0.0349	−0.1572	0.2078	0.0817	−0.1247	0.3237	0.2943
ER2	0.0545	**0.5822**	0.1507	0.0224	−0.0131	0.0852	0.1004	−0.0014	−0.0389	0.2539	0.077	0.1577	0.1244
FC1	0.3932	0.2124	**0.8109**	0.075	0.3362	−0.0839	0.2225	0.1112	−0.0384	0.1023	−0.0666	0.3962	0.3964
FC2	0.3369	0.2033	**0.8124**	−0.0155	0.1919	0.0188	0.1845	0.1385	−0.0501	0.1204	0.0943	0.1047	0.2224
FC3	0.2917	0.034	**0.8413**	−0.0782	0.1506	0.0567	0.2955	0.269	−0.1368	0.1704	0.0789	0.1359	0.1776
INT1	−0.2252	0.2467	0.0239	**0.8914**	0.5824	−0.4879	−0.27	−0.3065	0.6886	−0.2158	−0.3787	0.3616	0.4441
INT2	−0.2516	0.2462	0.0123	**0.8968**	0.466	−0.4007	−0.1196	−0.1762	0.5626	−0.0905	−0.2409	0.2383	0.3033
INT3	−0.3124	0.1824	−0.0424	**0.9044**	0.5483	−0.365	−0.1983	−0.2101	0.6838	−0.0487	−0.3467	0.1838	0.0872
INT4	−0.2002	0.1764	−0.0492	**0.9043**	0.5755	−0.4097	−0.329	−0.2263	0.652	−0.1407	−0.3095	0.1758	0.2399
IS1	−0.1166	0.0981	0.1176	0.5313	**0.8566**	−0.542	−0.4172	−0.2375	0.6083	−0.2976	−0.356	0.3432	0.2508
IS2	−0.0114	0.1277	0.2771	0.4428	**0.8682**	−0.3304	−0.1194	−0.0554	0.4285	−0.0511	−0.1865	0.4036	0.3045
IS3	−0.0274	0.0711	0.3189	0.5572	**0.8296**	−0.2875	−0.1731	−0.0917	0.4979	−0.0983	−0.2412	0.2149	0.1735
ITU1	0.3095	−0.2145	0.0525	−0.4383	−0.4382	**0.9454**	0.385	0.4971	−0.3805	0.4678	0.5932	−0.3749	−0.2067
ITU2	0.1896	−0.0882	−0.0604	−0.4199	−0.4371	**0.912**	0.2808	0.3348	−0.4989	0.4062	0.4716	−0.4281	−0.1726
PB1	0.2312	−0.0861	0.2408	−0.2043	−0.2675	0.2203	**0.8823**	0.3827	−0.3166	0.4636	0.2803	−0.0116	−0.076
PB2	0.2613	−0.0051	0.3226	−0.255	−0.3372	0.4403	**0.908**	0.3801	−0.297	0.4817	0.3162	−0.0744	−0.0467
PB3	0.2119	0.0087	0.224	−0.2253	−0.1949	0.3054	**0.8883**	0.2722	−0.293	0.5442	0.2574	0.0012	−0.1165
PE1	0.3955	−0.1055	0.0751	−0.1404	−0.1253	0.3198	0.3704	**0.8832**	−0.1813	0.5527	0.5862	−0.2058	−0.1584
PE2	0.4758	−0.1165	0.1917	−0.201	−0.2342	0.4227	0.2735	**0.7899**	−0.2633	0.3575	0.4896	−0.2109	−0.0867
PE3	0.5169	−0.1691	0.3202	−0.3186	−0.0736	0.4347	0.3235	**0.856**	−0.328	0.4668	0.6259	−0.1978	−0.0673
PPR1	−0.2942	0.0953	−0.0305	0.6201	0.5648	−0.4746	−0.2079	−0.2608	**0.9009**	−0.2675	−0.383	0.3611	0.1482
PPR2	−0.3657	0.2798	−0.123	0.6832	0.5839	−0.3872	−0.3531	−0.3126	**0.9586**	−0.1944	−0.3472	0.3181	0.1242
PPR3	−0.2603	0.1735	−0.1231	0.6861	0.5444	−0.425	−0.371	−0.2499	**0.8992**	−0.1361	−0.2678	0.2499	0.1673
PU1	0.4854	0.0436	0.276	−0.2068	−0.1517	0.4357	0.5172	0.5648	−0.2071	**0.8372**	0.5272	−0.2047	−0.268
PU2	0.2269	0.0709	0.0723	0.0094	−0.1149	0.3673	0.4152	0.4859	−0.0882	**0.8769**	0.4688	−0.1492	−0.2862

Table 6 (continued)

	EE	ER	FC	INT	IS	ITU	PB	PE	PPR	PU	PV	RE	SUE
PU3	0.1273	0.12	0.0514	−0.1301	−0.2203	0.3975	0.4755	0.354	−0.2438	**0.842**	0.3766	−0.2217	−0.2829
PV1	0.198	0.0701	−0.0015	−0.1328	−0.1103	0.3292	−0.0045	0.3857	−0.0909	0.2786	**0.6213**	−0.2178	−0.0786
PV2	0.424	−0.0809	−0.0062	−0.2858	−0.2544	0.4785	0.2155	0.5393	−0.3239	0.3921	**0.9258**	−0.3077	−0.1746
PV3	0.2904	−0.0982	−0.0342	−0.3726	−0.3652	0.521	0.3081	0.5958	−0.3657	0.5128	**0.8872**	−0.3824	−0.3776
PV4	0.5008	−0.1933	0.1576	−0.3375	−0.2784	0.5698	0.4101	0.6871	−0.3471	0.5602	**0.8914**	−0.3212	−0.1986
RE1	0.0336	0.1956	0.1868	0.0795	0.3242	−0.0978	−0.0607	−0.0336	0.1452	−0.0808	−0.1479	**0.5758**	0.4727
RE2	−0.1285	0.2284	0.127	0.2843	0.2685	−0.3883	−0.0918	−0.2772	0.3507	−0.27	−0.3386	**0.9074**	0.3457
RE3	−0.0455	0.3509	0.3371	0.1983	0.3424	−0.439	0.0912	−0.1744	0.2371	−0.1232	−0.3433	**0.812**	0.3034
SUE1	0.1579	0.275	0.3034	0.3047	0.2967	−0.1394	−0.0361	−0.0715	0.1618	−0.2363	−0.2299	0.3862	**0.9249**
SUE2	0.1619	0.2483	0.2164	0.2266	0.1941	−0.2541	−0.1503	−0.1829	0.1315	−0.3798	−0.2537	0.4123	**0.8611**
SUE3	0.1759	0.1683	0.4689	0.0969	0.1923	−0.0833	0.0206	−0.0061	−0.0125	−0.1632	−0.1377	0.2571	**0.6465**

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