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Intent and the Use of Wearables in the Workplace – A Model Development

by

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December 2018

Presented at: 14th International Conference on Wirtschaftsinformatik (WI), Siegen, Germany, 2019

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WI-892

Intent and the Use of Wearables in the Workplace – A Model Development

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Abstract. Due to reasons like demographic changes and variations in the spectrum of illness, worldwide expenditures in the health market have exploded. Contemporary information systems are evolving rapidly in the field of ubiquitous computing and nowadays support health in various fields. Wearables and tracking technologies have emerged in private life for health and fitness support. This adoption reveals future possibilities for innovating the health-supporting systems in the workplace. The crucial point of introducing wearables in the occupational health management system is the acceptance of employees. This paper provides a literature-driven measurement model to explain the behavioral intention to use wearables in the occupational health management system. The model provided is supported by 17 hypothesized relationships between relevant constructs and validated by card-sorting.

Keywords: Wearables Devices, Occupational Health Management, Technology Acceptance

1 Introduction and Motivation

Demographic developments are changing the labor market and employee demands on the working world. The world population is ageing, and the proportion of young skilled workers in developed countries is shrinking [1]. As a result of demographic change and changes in the spectrum of illnesses towards chronic degenerative diseases such as diabetes, degenerative musculoskeletal disorders, psychologically manifested diseases and addictions [2], health expenditure is at a record level [3]. In addition, a change in the value system of young employees toward more individuality and work-life balance can be observed [1]. The progressive digitalization requires an increased work speed, greater flexibility, and above all permanent willingness to learn and perform on the part of employees [1]. Not only since increases in digitalization has the workplace has been identified as the leading cause of many mental or psychological illnesses, as well as the primary cause of stress [4]. Various burdens on employees, as well as the developments mentioned above, entail an increased risk of long absences of employees in companies [5]. Workers with poor physical or mental health are often less productive, make worse

14th International Conference on Wirtschaftsinformatik,
February 24-27, 2019, Siegen, Germany

decisions, and have more absenteeism overall [6]. The employee absenteeism development in Germany illustrates this problem, which is of great economic relevance.

One way of reducing sick leave and creating additional incentives for employees in times of skilled-worker shortage is the introduction of an innovative occupational health management system (OHM). Both science and practice have recognized the significant positive influence of OHM on employees and organizations [7, 8].

At the same time, wearables are becoming increasingly popular with the majority of employees [9]. Research on intelligent portable systems has therefore increased in the health sector under the headings electronic health (eHealth) and mobile health (mHealth), as well as in industry [10]. This trend towards wearables can be seen in the high number of wearable manufacturers and strong industry growth.

Meanwhile, some companies are offering their employees the opportunity to participate in digital health programs in the workplace while following their health and fitness activities through wearables [11]. Studies have already shown that wearables can improve the health and well-being of individuals: Participants in health programs are happy to monitor, track and review their health data and the control of personal health data also encourages participants to behave healthier [12]. Similarly, it was found that the tracking and observing of one's physical activity, for example, leads to an increase in steps taken [13]. Furthermore, health programs which use portable devices increase the average employee participation from 20% to 60-70% [14].

Mainly due to their unique characteristics, wearables are very suitable for supporting the OHM of the future. Wearables can be worn on the body and can be used freely at work. In addition, the devices are mobile, always active and often context-sensitive. Furthermore, employees can use wearables in all areas of the company so that an organization-wide OHM is possible. Also, the possible use of gamification strategies [15] to increase employee motivation and the possibilities for personalizing health care through wearables are also promising.

However, from the employees' perspective, there are serious barriers which prevent participation in company health promotion measures. Many employees do not recognize the benefits of the measures or perceive OHM as paternalism and are afraid to embarrass themselves. Notably, the use of wearables which collect health data could be perceived as a high risk by employees. The fear of health data being misused (e.g., due to inadmissible performance monitoring of employees, as justification of salary increases, promotions or dismissals) based on the data collected is high and requires trust in the employer.

Against this background, the relevance of employee acceptance for new technologies at OHM becomes clear. Technologies and wearables cannot help to improve individual health if employees do not accept and use the technology provided. Some studies are already investigating the acceptance of wearables [3, 16, 17] and other portable technologies in healthcare [4, 18, 19]. Whereas the previous studies serve as valuable starting points, some specific aspects in the use of wearables in the working environment are missing or measure individual consumer's acceptance. Knowing the employee's level of acceptance for specific measures is necessary to increase the success of OHM. Companies must be able to predict employees' acceptance of wearables. However, as far as we know, there has been no empirical research on the acceptance of using wearables for health promotion in the workplace.

Based on a systematic literature review, we set out to deductively develop a research model that will help us to gain a better understanding of wearable acceptance in the workplace. The remainder of this paper is structured as follows: The next section describes the underlying theoretical foundations based on previous literature. The succeeding section introduces the research process, which is followed by the structural model development section. Subsequently, we provide insights into the measurement model development before we conclude with our discussion and outlook.

2 Relevant Work

2.1 Wearable Technologies in Healthcare

Wearables are specific technologies of the Internet of Things (IoT) and a concretization of ubiquitous computing aimed at improving our environment through visible or invisible, networked and intelligent electronic devices which enable a new form of human-computer interaction [20]. There are several different kinds of wearable definitions. However, for our purpose, we define wearable devices as electronic devices that can be worn on the body and measure via one or more sensors physical activities or health conditions and are (wirelessly) connected to other computers or smart devices [21]. The sensors collect a broad range of different data, such as various vital signs, physiological parameters, and environmental conditions [22, 23].

In addition to the use of wearables in health science, there are also many other fields of application, e.g., consumer goods [24], in the fields of professional and recreational sports [25], and for authorities with security tasks [26]. Within the application of wearables in the health context, a large number of overlapping terms are used. The most common definition defines eHealth as "an emerging field in the intersection of medical informatics, public health and business, referring to health services and information delivered or enhanced through the Internet and related technologies. In a broader sense, the term characterizes not only a technical development, but also a state-of-mind, a way of thinking, an attitude, and a commitment for networked, global thinking, to improve healthcare locally, regionally, and worldwide by using information and communication technology" [27, p.1]. Although there are differences between the terms, it is accepted in research to refer to eHealth as an all-encompassing term for telemedicine and mHealth and includes various forms of HIT [10].

The concepts of workplace health prevention and health promotion are complementary and overlap in many respects and therefore are partly used synonymously in practice. We refer to OHM which includes both concepts. A trend towards digitalization is discernible, not only in the health sector, but also in the area of OHM [28]. This digitalized health promotion is a possible field of application for digital health technologies. Modern technologies open up new opportunities for OHM in the areas of requirement analysis and employee awareness.

While OHM causes an increase in the health affinity of employees, promotes high participation rates, and can reach all employee target groups, criticism exists with regard to data privacy [4, 29]. One of the biggest challenges in OHM in connection with wearables relates to the solution of IT security issues, data protection concerns, and legal and ethical difficulties in handling the data. In most cases, wearables forward data to the manufacturer, third-party providers and intermediaries (e.g., insurance companies, scientists, advertising companies, and, in the case of the present work, the employer). The gathered data is often stored decentrally in a cloud. Hence, employers need to guarantee system security and assure data privacy.

In summary, the voluntary and private use of wearables for individuals who are interested in improving their health and fitness is not new. However, the wearables' usage during work and the integration in an OHM become more and more important [30]. The employees' acceptance is essential for an effective wearable usage in OHM. Empirical studies which examine the employee acceptance of OHM with wearables are surprisingly scarce, which is why we set out to deductively develop a concise structural equation model in the following sections.

2.2 Health Behavior

Regarding the field of health behavior, four main theories are used: (1) the Health Belief Model, (2) the Protection Motivation Theory, (3) Subjective Expected Utility Theory and Theory of Reasoned Action [31]. Each of the four theories assumes that an expected negative health event and the desire to avoid or reduce this occurrence will motivate self-protection. Furthermore, they explain health-related behavior on the basis of the expected value theory and the cost-benefit analysis. The Health Belief Model assumes that a person who decides to perform a health-related action takes the action from a consideration of the perceived health threat that occurs when the action is omitted and the belief in the effectiveness of the proposed measure, minus perceived barriers [32].

Moreover, the Health Belief Model is used to develop health promotion measures [33]. It incorporates four basic constructs: perceived susceptibility, perceived severity, perceived benefits and costs, and perceived barriers. The Protection Motivation Theory uses similar factors to explain health behavior (perceived vulnerability, perceived severity, response efficiency, response costs) [34] and in addition, the determinant self-efficacy is integrated into the Protection Motivation Theory. The Health Belief Model's perceived benefits and Protection Motivation Theory's response efficacy measure the same underlying construct and can be equated with the performance expectancy construct of Unified Theory of Acceptance and Use of Technology (UTAUT) [35]. It is argued that the Health Belief Model's perceived benefits are equivalent to the two determinants intrinsic and extrinsic motivation of UTAUT2 [4]. Further determinants also determine preventive health behavior. The Health Belief Model's supplementary determinants include, as preceding factors, e.g. the demographics of the individual, psychological factors, the mediator variable cues to action, advice on health, a letter from the doctor, or an emerging illness within the family or circle of friends, as well as the mediator variables self-efficacy, response efficacy and the value of action [36].

Furthermore, preventive health behavior is influenced by response efficacy and self-efficacy, as well as health motivation and health consciousness [36]. Health motivation "refers to consumers' goal-directed arousal to engage in preventive health behaviors"

[36, p.9], while health consciousness "refers to the degree to which health concerns are integrated into a person's daily activities" [36, p.10].

2.3 Technology Acceptance

Many research disciplines are investigating the adoption or acceptance of innovations. Studies on the acceptance of technologies are regarded as the most important research field in information systems (IS).

In the field of economics, particularly in connection with innovation management, adoption is understood as the acceptance of an innovation by an individual customer. A positive decision to accept an innovation by users is therefore acceptance. There are different views in literature as to whether the attitude towards innovations, the intention of behavior or benefit, the behavior, or a combination of these factors should be regarded as acceptance. In economic acceptance research, the distinction between acceptance of attitudes and acceptance of behavior has, therefore, become established. The intention to use a technology is equated with attitudinal acceptance. Therefore, this type of acceptance is not directly observable by users and is, therefore, operationalized by the behavioral intention. In contrast, when adopting innovations in the form of observable behavior (e.g., the use of a wearable for OHM), acceptance of behavior is discussed. Acceptance is then determined by usage behavior. The wearable technology in the OHM context can be seen as (technical) innovations and can either be accepted or rejected by users, in our case employees. The acceptance of attitudes is operationalized as an intention to use or behave (behavioral intention). The role of behavioral intention as a predictor of behavior has been extensively researched in IS literature and related research fields [37–39]. Behavioral intention is defined as a measure of the strength of an individual's intention to conduct a certain behavior [40].

The rich literature on adoption of technologies, and in particular the proposed Technology Acceptance Model (TAM) of Davis [41], is being studied in detail by IS researchers. However, TAM is also criticized for being too parsimonious to reliably explain complex psychological processes such as behavior and human’s technology acceptance, and it does not take influences of social and personal control factors into account [38, 42]. The results of our literature review indicate that within the plethora of acceptance models there is only one study which provides a model for measuring acceptance of mHealth applications in the OHM context [43]. The study discusses the suitability of mHealth apps for the use in the OHM context and the underlying determinants that motivate employees to use health apps at the workplace. Based on TAM, the Health Belief Model, and the Theory of Planned Behavior, the authors propose a model to explain adoption behavior. However, it does not regard aspects of motivational theory and is quite complex, due to the inclusion of fifteen explanatory constructs. Furthermore, there is no empirical validation of the proposed model. Based on these findings, we take both the specific characteristics and the use of wearables in the context of OHM into account when designing our examination model. Therefore, we transfer existing studies of relevant other contexts and present an overview of acceptance research studies which are germane for our model development.

Since wearables are small body-worn computers and part of the IoT, studies on acceptance research in both areas, as well as studies on different types of wearables, are relevant for our model development. Many researchers have demonstrated the influence of intrinsic and extrinsic motivation, which are often operationalized as perceived enjoyment and perceived usefulness [44, 45].

In addition, a relevant study on the acceptance of IoT [29] and a study on ubiquitous, pervasive technologies [46] were identified. The acceptance of IoT measures the influence of perceived usefulness, perceived ease of use, social influence, and perceived behavioral control, which are equated in the study with the constructs of UTAUT, on behavioral intention. The authors supplement their model with the constructs trust and perceived enjoyment. The results confirm a strong influence of the UTAUT determinants, but a non-significant influence of trust on behavioral intention [29]. The study of ubiquitous technologies also confirm the strong influence of perceived usefulness and perceived ease of use on the behavioral intention of pervasive computers, but cannot confirm a significant influence of compatibility, perceived overall risk, and attractiveness of alternatives [46].

We also identified some studies on wearables. It is striking that most of the studies use different combinations of the UTAUT's main determinants. In addition, the perceived enjoyment construct and intrinsic motivation are often included in the models [3, 17, 47]. The determinants trust toward the employer [17] and other forms of trust [3], as well as different forms of risk [47], are also included in the models for predicting the behavioral intention of wearables. Summarizing, we observe a significant influence of the UTAUT determinants perceived usefulness, social influence, and perceived enjoyment. Within the acceptance research of eHealth technologies, there are also studies on the acceptance of wearable-related technologies [5, 48], such as mHealth technologies [35, 49, 50], Health Information Technology [18, 51], and Wearable Health Monitoring Systems [4]. In contrast, studies on the adoption behavior of health technologies for patients or consumers, which are essential to the requirements for an acceptance study of employees, are relatively rare [4, 50, 52]. Among these empirical studies on users' eHealth adoption behavior, most studies explain the usage behavior based on TAM [18, 50] and its extension UTAUT [4, 35]. The direct and indirect influence of perceived usefulness and perceived ease of use is confirmed in all empirically tested studies. Similar to the acceptance studies for wearables, perceived enjoyment and hedonic motivation were additionally included as determinants [4].

Whereas the identified studies and models serve as a valuable starting point, none of the presented studies focus explicitly on wearables in the OHM context and therefore take the specific requirements of the acceptance of wearables in the OHM into account.

3 Structural Model Development

Based on the scientific literature presented above, we derived our hypotheses and built our structural model. We combined the Health Belief Model, and the Motivation Model, and incorporated factors from UTAUT. We present our developed structural model in Figure 1.

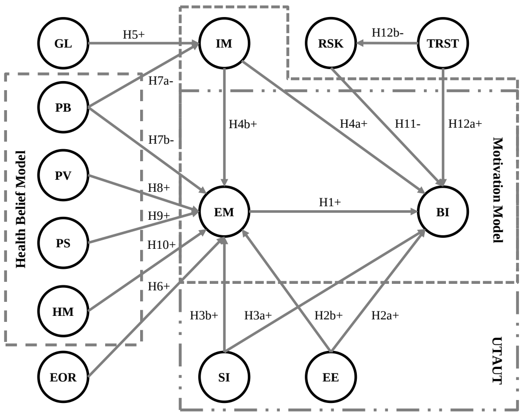

Figure 1. Structural model explaining the behavioral intention

With our model, we set out to explain our dependent variable *behavioral intention to use wearables in OHM* which can be seen as a predictor for acceptance. UTAUT takes the determinant extrinsic motivation of the motivation model as performance expectancy into account [39]. Extrinsic motivation is defined as "a construct that pertains whenever an activity is done in order to attain some separable results" [53, p.60]. Concerning wearables in OHM, extrinsic motivation is defined as the perceived probability that a wearable supports the employee in achieving its goals. Thus, we assume that the prospect of achieving these goals has a positive influence on the behavioral intention which is why we propose:

H1: Extrinsic motivation (EM) has a positive impact on the behavioral intention to use a wearable in OHM (BI).

The determinant effort expectancy [4] or the closely related construct perceived ease of use [29] was also identified as an essential factor for measuring acceptance. Effort expectancy is defined as “the degree of ease associated with the use of the system” [39, p.450]. In addition to the effort expectancy, social influence is also included in suitable acceptance models. The social influence is defined as the "extent to which consumers perceive that important others (e.g., family and friends) believe they should use a particular technology" [54, p.159] and hence, has an impact on behavioral intention and extrinsic motivation. We state that a wearable in OHM is a portable device for increasing and promoting health. We argue that friends and family have a particular interest in the individual employee's health. Thus, the close social environment motivates the individual to take part in OHM. The perceived social pressure and the opinion of an individual's environment have an impact on behavioral intention and extrinsic motivation. Thus, we conclude:

H2a: Effort expectancy (EE) has a positive impact on behavioral intention (BI).
H2b: Effort expectancy (EE) has a positive impact on extrinsic motivation (EM).
H3a: Social influence (SI) has a positive impact on behavioral intention (BI).
H3b: Social influence (SI) has a positive impact on extrinsic motivation (EM).

Intrinsic motivation is defined as "the doing of an activity for its inherent satisfactions rather than for some separable consequence" [53, p.56]. Accordingly, it represents the extent to which employees perceive wearables in OHM, apart from other consequences, as pleasant and entertaining. Studies on consumer behavior as well as research in the field of IS have found that intrinsic motivation is an essential determinant for explaining technology acceptance [54, 55]. Furthermore, in the context of mHealth services and also in the context of wearables, it is shown that the user's intention to use mHealth services is determined by both extrinsic and intrinsic motivation [3, 29, 47, 49]. Thus, if an employee has intrinsic motivation to improve his or her health, it is all the more likely that he or she will participate in OHM activities and take greater account of the benefits provided [56]. We include intrinsic motivation in our model and state that an activity perceived as pleasant or entertaining has a positive influence on the perception of the usefulness and thus, supports a user to achieve its goals. Thus we hypothesize:

H4a: Intrinsic motivation (IM) has a positive impact on behavioral intention (BI).

H4b: Intrinsic motivation (IM) has a positive impact on extrinsic motivation(EM).

When introducing a wearable in OHM, it is crucial that the use of the device is accepted by employees as quickly as possible. So it is vital to convince employees to adopt technological innovations at an early stage. We consider employees with a high motivation to use different technologically innovative devices as gadget lovers. A gadget lover is defined as "a consumer with high intrinsic motivation to adopt and use a variety of leading-edge, technology-based goods, including the services that complement them" [57, p.330]. So far, the gadget-loving concept has yet not been integrated into acceptance research. We incorporate gadget loving as an external variable which measures the employee's personal characteristics. Hence, we postulate:

H5: Gadget loving (GL) has a positive impact on intrinsic motivation (IM).

From the perspective of the extrinsic motivation, a behavior is carried out on the basis of the expected benefit of the action or the expected advantages that an action brings [53]. Expected organizational rewards can be regarded as fundamental objectives of extrinsically motivated behavior [58]. Rewards are also often used in the OHM context to motivate employees to participate in specific measures [6]. These expected organizational rewards can range from monetary incentives, such as discounted membership in gyms, to points in competition with other employees. Thus, the offered rewards shall motivate employees' participation. Hence, we conclude:

H6: Expected organizational rewards (EOR) have a positive impact on extrinsic motivation (EM).

Furthermore, we also included the Health Belief Model in our model. It proposes that perceived barriers are subtracted from the perceived benefits [32]. The negative aspects of a health-promoting activity can act as barriers to the implementation of the recommended behavior. Consequently, if employees consider OHM activities as, for example, unpleasant or time-consuming, their motivation will decrease. On the basis of a cost-benefit analysis, the advantages of preventive measures are weighed against their disadvantages. Since the perceived benefits of the preventive measure are already taken into account by the constructs intrinsic and extrinsic motivation [4, 35], we only include the perceived barriers into our model. Thus, we hypothesize:

H7a: Perceived barriers (PB) have a negative impact on extrinsic motivation (EM).

H7b: Perceived barriers (PB) have a negative impact on intrinsic motivation (IM).

Furthermore, we integrated the effects of the perceived health threat, operationalized as perceived severity and perceived vulnerability, into our model. Perceived vulnerability is defined as the perception of an individual's vulnerability to health threats, while perceived severity is defined as the assessment of an individual as to whether a particular health threat is severe or dangerous [59]. From the perspective of extrinsic motivation, the expected benefit of an action determines the behavior. Employees are expected to value the benefits of the use of wearables in OHM more if the expected consequences of a resulting health threat are serious. Hence, we state:

H8: Perceived vulnerability (PV) of an individual has a positive impact on extrinsic motivation (EM).

H9: Perceived severity (PS) of an individual has a positive impact on extrinsic motivation (EM).

We also incorporate health motivation into our model, which "refers to consumers' goal-directed arousal to engage in preventive health behaviors" [36, p.9] and hence, refers to the internal characteristics. Studies have found that this can be associated with most health behaviors [36]. This preventive health behavior is of great importance to many individuals and represents an essential general goal in life. Hence we conclude:

H10: Health motivation (HM) has a positive impact on extrinsic motivation (EM).

According to the literature on wearables, risk has a significant influence on the behavioral intention of individuals [4, 47]. Within the acceptance research of health-related IT, the fear of unintentional secondary data use and privacy concerns are often investigated [4, 29, 49, 60]. For example, in the case of restructuring measures, employees face the risk that the employer will incorporate the gathered health data in its redundancy decision. Therefore, we define risk as the total perceived threats that employees feel when using wearables in OHM. Hence, we postulated that risk has a negative influence on behavioral intention. Thus, we conclude:

H11: The perceived risk (RSK) has a negative impact on behavioral intention (BI).

The long-term exchange of personal information (e.g., with the employer) through the use of wearables in OHM also requires a trustful relationship between the employee and its employer. In the context of eHealth technologies and also in technology acceptance studies, it is confirmed that the effect of trust is a decisive factor [60, 61]. We argue that employees, in particular, are often in a weaker position than their employers. Especially in our context, highly personalized user data is collected, and there is the chance that the employer may misuse this data. We define trust as the perception of the employee that its employer is trustworthy and wants to do something good for its employees by introducing wearables in the context of OHM. Since trust has a significant influence on the behavioral intention of individuals we thus conclude:

H12a: Trust in the employer (TRST) has a positive impact on behavioral intention (BI).

H12b: Trust in the employer (TRST) has a negative influence on perceived risk (RSK).

4 Measurement Instrument Development

The development of a suitable measurement model is crucial for the causal model's future evaluation. The development of our measurement instrument is therefore carried out in several stages [62]: (1) We identified existing measurement scales where possible and initially created new ones where necessary. The measurement scales for the latent variables are expressed by several manifested statements (items) [63]. (2) Subsequently, we adapted the identified items to our context and gained an initial item long-list. (3) Subsequently, three scientists iteratively reviewed the initial item pool and adjusted the items to fit our context and provide a common style in language and wording. (4) Following this, we conducted a card-sorting procedure proposed by Moore and Benbasat [62]. The card-sorting procedure aims to assess the construct validity of the various scales and to "attempt to identify any particular items which still may have been ambiguous" [62, p.199]. Therefore, we sent out an Excel-spreadsheet containing a VBA macro for randomization via email and asked twelve judges to sort the randomized initial item pool to the corresponding construct with given construct definitions [62, 64]. The group of judges consisted of employees in order to ensure that the items to be evaluated were understandable for future participants. In a second step, after the judges had assigned the items to the corresponding constructs, we asked them to sort the items of each construct according to their representativeness, to then identify the most appropriate items of the initial long-list, and then to send back the spreadsheet. After having received the completed card-sorting, we consolidated the filled-out spreadsheets and analyzed the results. This enables the identification of items which are not suitable to measure the underlying construct. It is assumed to exclude these items from the study [64]. After having received the results, we evaluated the construct validity of our initial item pool and removed items which were mainly sorted into an incorrect construct. (5) Finally, we pilot-tested the resulting item pool with a seven-point Likert-scale and analyzed the gathered feedback to complete our instrument. Thus, we ended up with a total of 51 items for our final measurement model. Table 1 provides the sources and number of items for the final measurement model.

Table 1. Sources of the measurement model

Construct	# of items	Adapted from
Behavioral Intention	4	[41, 65]
Extrinsic Motivation	4	[41, 66]
Effort Expectancy	4	[41, 65]
Social Influence	4	[39]
Intrinsic Motivation	4	[65, 66]
Gadget Loving	4	[57]
Expected Organizational Rewards	4	[67], own
Health Motivation	4	[68, 69]
Perceived Barriers	5	[70, 71], own
Perceived Severity	3	[70]
Perceived Vulnerability	4	[70]
General Risk Beliefs	3	[72]
Employees Trust Beliefs	4	[1]
Total	51	

5 Conclusion and Further Research

In this article, we set out to develop a literature-based measurement model to explain the behavioral intention to use wearables in OHM. As highlighted in the first section, due to demographic developments as well as changes in the spectrum of illness and in the value system of employees, health expenditures in industrialized countries like Germany have exploded. The introduction of modern, easy to use and consumer-centric IS in the workplace possibly meet these challenges. IS, such as wearables, do have the functionality to support employees' health conditions. Consequently, the crucial point of introducing wearables in the workplace for OHM purposes is the employees' behavioral intention to use the provided technologies.

As the presented work shows, many studies exist on the acceptance of several kinds of technologies. Although the possibilities of supporting the health of users by IS are highly relevant, research is surprisingly scarce. Therefore, we reviewed the current state-of-the-art of wearable technologies, health behavior, and technology acceptance from the perspective of possible applications in the workplace. Subsequently, we developed a measurement model to explain the behavioral intention to use wearables in an OHM context. The measurement model was validated by a card-sorting procedure and led to a measurement model consisting of a total of 51 items. With our model, we provide a research tool to explain the behavioral intention to use wearables in OHM. Regarding our specific next steps in this research endeavor, we deem quantitative-empirical methods as most applicable to validate our model. Therefore, we will collect data by conducting a large-scale multinational online survey study and analyze the gathered data using a structural equation model approach [73] and will subsequently strengthen our statistical analysis by conducting multi-group comparisons [74]. The survey will incorporate different kinds of wearables such as wristbands and smart clothing. Hence, differences in wearable technologies in the behavioral intention to use might be identified, and practical implications can be derived. Furthermore, we will apply the research model in different industries and different organizations to gain a deeper insight into under which conditions employees accept the implementation of wearables for OHM. To get a more comprehensive view on the intention to use wearables in the workplace, different theories (e.g., system theory) from related domains could be taken into account as OHM affects a lot of different perspectives, habitats, actors, and systems.

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