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How individuals perceive and process diagnostic device errors

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ABSTRACT
Diagnostic device errors by health wearables cannot be avoided entirely, but they can have dramatic consequences for individuals, who are, consequently, deeply concerned and may refrain from using. However, it remains unclear how individuals assess and respond to potential diagnostic device errors when adopting health wearables. The present study unpacks this 'black box' using the elaboration likelihood model (ELM) to evaluate how potential diagnostic device errors translate into error perceptions, error processing, and behavioural reactions enacted through central and peripheral route cues. Based on a survey of 193 people with diabetes, we unveil that while peripheral cues are activated, most of the error processing is conducted consciously, strongly contributing to individuals' attitude formation towards health wearables and their usage intention. These insights improve our theoretical understanding of user perceptions and responses to potentially erroneous health wearables. Furthermore, they guide suppliers in optimising their strategic product development and communication strategies.

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Diagnostic device errors; health wearables; error perceptions; error processing; elaboration likelihood model

1. Introduction

Health wearables include smartwatches, patches, chest straps, wristbands, and others. They are frequently used for monitoring cardiometabolic health based on indicators such as heart rate, glucose, and electrocardiogram, as well as respiration, sleep, diet, or specific symptom monitoring (M. A. Lee et al., 2023). However, not only for health wearables, system errors remain a major obstacle to system adoption and usage, and are often not fully avoidable, for technological (e.g. underlying data is subject to measurement error) or economic reasons (e.g. if the elimination of the errors would entail unacceptable costs). Diagnostic device errors are system-related errors during the diagnostic process that are caused by the technological abilities of the involved health IT. In a domain as critical as personal health, understanding how users perceive and respond to IT errors is essential since such errors can substantially affect physician-patient relationships (Dave et al., 2021; Kistler et al., 2010) and even be lethal (Cryer, 2002), e.g. if a patient were erroneously advised to take an incorrect dose of medicine.

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Patients are interested in keeping the diagnostic device error rates low but are often not free to choose the medical equipment themselves. Acceptance and trust in the data that patients obtain from such devices are highly relevant in digital health ecosystems (Solberg et al., 2022). Unlike in the professional context, in the private context, individuals can freely choose which health wearables they want to use. Factors of performance expectations, effort expectancies, social influence, healthcare threat, and trust significantly impact patients' intention to adopt healthcare IoT (Dadhich et al., 2022). By making their own choice on healthcare devices, individuals may thus directly influence the level of potential diagnostic device errors they are exposed to.

While prior research has examined the economic consequences of diagnostic device errors and health wearables' accuracy or provided technological recommendations for improving error margins (Rodbard, 2016), only little research has focused on the impact of such technology-induced hazards on user behaviour. Bitkina et al. (2020) presented an overview of the current state and the future challenges within medical devices' usability and user experience. The paper points out the importance of improvements in reliability and safety on medical devices for the health care system but also highlights the necessity to carefully consider the user side in all development stages of medical devices. Also, from usability research on personal digital assistants in health care, we know that errors are one of five critical elements: learnability, efficiency, memorability, and satisfaction (Lindquist et al., 2008). We still miss a deeper understanding of how diagnostic device errors are perceived and what kind of decision processes this institutes. Even more, we do not know whether users take such decisions consciously and how they balance the potential pros and cons when deciding on using health wearables. We ask: *How do individuals perceive and process diagnostic device errors?*

To answer these research questions, we surveyed 193 people with diabetes. For these individuals, digital self-monitoring of their health status is an integral part of their disease management, while diagnostic device errors can have severe consequences. To uncover how these individuals process diagnostic device errors and how this affects their attitude towards and their usage of health wearables, we use an elaboration likelihood model (ELM) to distinguish between central (more conscious and thoughtful) and peripheral (less conscious and thoughtful) process routes. We examine the effects of potential hazards arising from using potentially erroneous health wearables on users' decision-making. We also explain how individuals process these technology-induced hazards, providing suppliers with more insights on how to communicate potential error levels to users.

2. Conceptual foundations

2.1. Diagnostic device errors and their consequences

Given the rising impact of IT in the health domain, e.g. the development of wearable blood pressure monitoring rings (Sel et al., 2023), health wearables can be a means to reduce diagnostic errors but also a missed opportunity to make timely or correct diagnosis (Singh, 2014) but also constitute the source of diagnostic errors (Fontil et al., 2019). Diagnostic device errors are caused by health wearables' technological abilities and occur during the diagnostic process as total measurement errors if the variable is continuous or misclassifications if the variable is discrete (Yang et al., 2018). Unfortunately, health wearables have error margins of up to 30% (Takacs et al., 2014).

Diagnostic device errors can be very costly for healthcare systems when they cause misdiagnosis-related harm, which is 'preventable harm that results from the delay or failure to treat a condition actually present (when the working diagnosis was wrong or unknown) or from treatment provided for a condition not actually present' (Newman-Toker & Pronovost, 2009, p. 1060). Concrete consequences can range from no or little harm to severe harm (including death) and include psychological and medical costs to patients, malpractice claims to physicians, and incurred financial costs for healthcare systems. For people with diabetes, diagnostic device errors can potentially lead to acute hypoglycaemia or hyperglycaemia, and the individuals may fail to seek the needed services or treatment and run the risk of permanent functional impairment (Cryer, 2002). Considering healthcare systems, if people with diabetes use the least accurate blood glucose monitors, this would lead to additional annual costs in the U.S. of approximately $339 million for Type 1 patients and approximately $121 million for Type 2 patients (Budiman et al., 2013). Diabetes mellitus affected 537 million people globally in 2021, and over 6 million deaths occurred. Forecasts predict that 643 million people will have diabetes by 2030, which is 1 out of 9 adults. Therefore, research on diabetes plays an important role, and it utilises the most recent technological trends, such as forecasting blood glucose levels using artificial intelligence (Ahmed et al., 2023).

2.2. Information processing of diagnostic device errors

By collecting personal health information from a broader population and analysing it in real-time, health wearables provide instantaneous, goal-oriented feedback that can help individuals better understand their health status and identify possibilities to support healthy behaviours (Piwek et al., 2016). The adoption of wearable devices increases quickly (Kaplan et al., 2023), making it important to understand the impact of such devices. Among others, wearable devices were associated with improved health perception, self-care (Hydari et al., 2023), and longer workout duration, which in turn helped reduce psychological distress (Choudhury & Asan, 2021). Along with other medical devices and online platforms, health wearables also profit from recent advancements in wearable technologies and AI to enable individuals new possibilities of medical self-diagnosis (Aboueid et al., 2019). However, since the sensor capacities for health wearables are still in their infancy, diagnostic device errors cannot fully be avoided, and so it is not only the personal health information but also their sensitivity to being flawed that individuals need to consider when using health wearables. Although diagnostic device errors play a key role in individuals' satisfaction with health wearables, there is insufficient knowledge about how individuals perceive them and process them as part of their technology usage decisions. Applying dominant IS acceptance models as well as theories of attitude formation (Bandura, 1993; Rogers, 1983) is not suitable to shed more light since they focus only on reflective precursors of action and assume that changing a person's conscious cognitions will lead to substantial changes in attitudes and behaviours. Since these cognitive approaches have shown insignificant explanatory power, dual process models have been developed to distinguish a conscious (central) and an unconscious (peripheral) path in information processing (Hagger, 2016). Following such dual process perspectives, individuals may process potentially erroneous health information along two routes: first, the more thoughtful and cognitively effortful route that is used when individuals are both motivated and able to think about the consequences of misdiagnosis-related harm (central route); second, the less thoughtful and cognitively effortful (peripheral) route, which dominates when motivation or ability are low and affects dominate (Petty & Cacioppo, 1986; Strack & Deutsch, 2004). In IS research, dual-process theories have frequently been used to explain how recipients process received information, indicating a high fit to explain how individuals process specific information, such as (erroneous) health information (Hagger, 2016; Sheeran et al., 2013). Therefore, this dual-route processing is directly triggered by individuals' error perceptions, which are the mental representation of the diagnostic device errors. Thus, individual error perceptions are followed by dual-error processing over central and peripheral routes, eventually affecting individuals' attitude formations and usage intentions.

3. Research model and hypothesis development

3.1. Research model

As the basis for our research model, we use the elaboration likelihood model (ELM), which, unlike many other models commonly used to study consumer behaviour, explains how messaging affects changes in individuals' attitude and their decision making (Shahab et al., 2021). Originally developed in the early 1980s (Petty & Cacioppo, 1986), the ELM is one of the most prominent dual process models that explain individuals' information processing (Figure 1). A dual process model explicitly allows us to distinguish conscious from unconscious processing alternatives to understand more of the level and depth of use processing while dealing with errors. ELM suggests that a person has a continuum of elaboration approaches to processing information. Individuals may elaborate on issue-relevant thinking or use simple decision rules to respond to this information. The nature of elaborative processing goes beyond simply paying attention to or comprehending the arguments in the message. Elaborative processing involves generating one's own

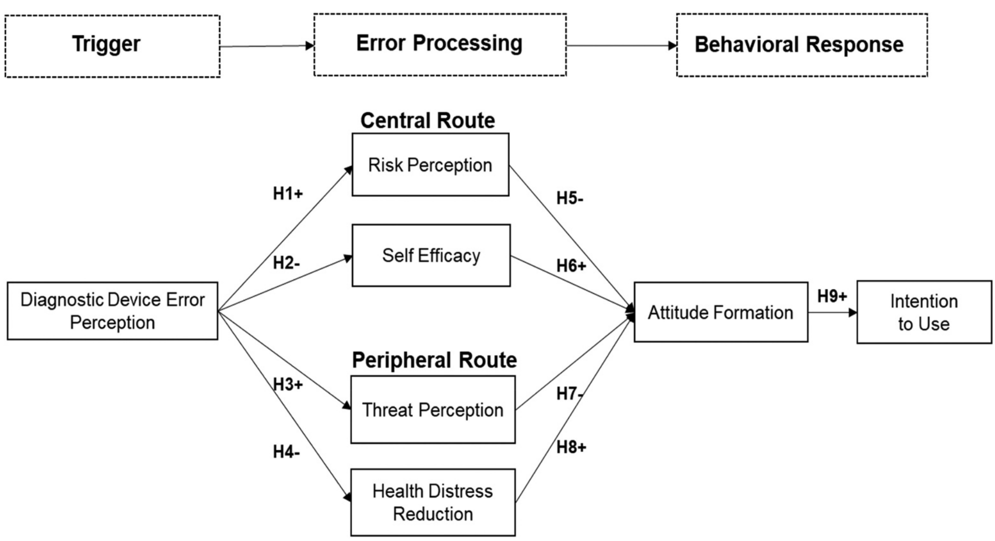

Figure 1. Conceptual research model.

thoughts in response to the information to which one is exposed. ELM has been successfully applied in similar research fields, providing a detailed understanding of how information processing is conducted and which cues are affected (Angst & Agarwal, 2009; Bhattacherjee & Sanford, 2006). Using mobile health applications as an example, ELM has also been used to show that information and system quality affect persistent use and are processed on two routes (Guo et al., 2020).

We use the ELM conceptualisation of Tam and Ho (2005) and integrate established variables with high contextual fit on both routes. The focus of error processing through the central route is closely linked to individuals' perceived desirability of the consequences and the perceived likelihood that these consequences will occur (Ajzen & Fishbein, 2000). Research suggests that risk perception is a suitable measure to assess the negative effects about IT derived from central route processing (Rhodes & Pivik, 2011). Since diagnostic device errors are directly tied to individuals' wellbeing, occurring risk perceptions are an inherent attribute of health wearables adoption. However, despite health wearables' advantages for individuals, such as the more convenient measurement or automatised data analysis and storage, proper handling of health wearables is a requirement. For the central processing, we therefore integrate self-efficacy (Schwarzer, 2014), as an important antecedent of technology adoption and usage decisions in healthcare (Zhang et al., 2018) to account for individuals' perceived capability to perform a target behaviour (Johnston & Warkentin, 2010). However, the central route is only taken when error processing is based upon critical thinking and the triggering information of diagnostic device errors is given due consideration. The recipient scrutinises all available information relevant to the message. If recipients lack either the motivation or the ability to process the detailed information concerning the diagnostic device error, they engage in peripheral processing. To account for these rather simple cues for judgement formation, we use threat perception, as an emotional feeling that serves as the non-calculable affective counterpart to risk perception (DeSteno et al., 2004). Again, for peripheral route processing, we not only cover potential negative effects but also seek to analyse individuals' balancing of potential positive and negative factors when deciding on health wearables usage. Chronic diseases, especially, often put substantial burdens and worries on patients, and health IT can help reduce this distress by providing effective support in self-management behaviour (Fisher et al., 2013). We therefore include health distress reduction as the second peripheral variable to account for the potentially positive functional effects of health wearables on individuals (Kendall, 2013).

3.2. Effects of error perceptions on error processing

Risk perception is 'the subjective belief that there is some probability of suffering a loss in pursuit of a desired outcome' (Pavlou & Gefen, 2004, p. 41). It can be driven by uncertainty about the potential consequences of acting on inaccurate information. Research has unveiled that quality of information (i.e. accuracy) can substantially reduce perceived risk in the context of information exchanges and web-based health information-seeking (Nicolaou & McKnight, 2006). Risk perceptions relate to potentially undesired effects of technology use and comprise a collection of notions that individuals form based on different risk sources and the information available to them (Nicolaou et al., 2013). Thus, risk perceptions are based on the potential risks arising from the use of health wearables, based on an assessment of the health information provided to them. It has been shown that insufficient information quality can trigger risk perceptions (Nicolaou & McKnight, 2006; Park et al., 2015). Based on this, we also expect a direct link between the perceptions of health wearables' sensitivity for diagnostic device errors and individuals' risk perceptions. We hypothesise:

H1: Error perceptions will positively influence risk perception.

Self-efficacy, defined as the perceived capability to perform a target behaviour, is a substantial predictor of various health behaviours and is proposed to be important for the self-management of chronic diseases (Lorig et al., 1999; Schwarzer, 2014). However, compared to its effects, much less is known about the predictors of self-efficacy. Concerning IS adoption, various behavioural, cognitive, and environmental factors have been found to influence computer self-efficacy; these include ill-defined performance levels, ambiguous feedback, and inaccurate information (Lam & Lee, 2006). In line with this, individuals' self-efficacy depends on accurate information for their disease self-management, which provides individuals with more independence and can help them to understand their disease better. Diagnostic device errors can lead to restrictions in individuals' self-management effectiveness and user complaints (Breton & Kovatchev, 2010). Qualitative research also suggests that only effective self-monitoring of personal health information positively affects perceived self-efficacy (Ong et al., 2014). Following this, error perceptions may decrease self-efficacy by impeding individuals' convenient self-management of their health status. Thus, we hypothesise:

H2: Error perceptions will negatively influence self-efficacy.

Researchers typically label an implication of present or future harm as a threat and predicate beliefs in its efficacy on the notion that certain effects follow as long as the threat is perceived by individuals (Johnston & Warkentin, 2010). Following Walter and Lopez (2008), we define individuals' perceived health threats as the extent to which individuals believe that using a health wearables will decrease their control over the conditions, processes, procedures, or content of their health status. In general, threat perceptions are a key predictor of responses to health information. Health and neuropsychology researchers have developed frameworks that account for the ways in which people respond to health information that individuals perceive uncomfortable or threatening (Rogers, 1983). For instance, these studies demonstrate that cognitive or attentional modulation of amygdala activation are evoked by emotional or threatening cues (Dvorak-Bertsch et al., 2009). Individuals perceive threats when viewing photographic images with negative valence, during negative emotional imagery, and during the anticipation of electric shocks (Curtin et al., 2001). We see diagnostic device errors as potential misdiagnosis-related harm that can cause further threat perceptions. Following previous evidence, we hold that threat stimuli caused by diagnostic device error perceptions may influence individuals' peripheral processing unless their cognitive capacity is essentially exhausted, and their threat cues are activated. We hypothesise:

H3: Error perceptions will positively influence threat perception.

Health distress refers to the frequently hidden emotional burdens, stresses, and worries associated with managing demanding, progressive, chronic diseases (Gonzalez et al., 2011). Research suggests that computer-based supportive interventions to improve self-management behaviours will reduce health distress, owing to a reduction of worries and concerns about poor disease management (Fisher et al., 2013). Owing to their support in individuals' self-management, health wearables should lower users' frustrations owing to disease-associated restrictions and make them feel more courageous and less afraid concerning the future development of their health status. A related aspect is that IT-based health-promotion technologies can help individuals better understand their stress sources and lower health distress (Bosworth et al., 1995). Providing detailed information on physiological activities (e.g. heart rate) can help users better adapt their stress-related physiological activities to improve their health. However, while correctly functioning health wearables have this positive potential for distress improvement, diagnostic device errors might inhibit these positive effects. In contrast, such errors might even create additional worries, making individuals fall into an aversive negative state in which coping and adaptation processes fail to return to physiological and/or psychological homoeostasis, and the extent of the distress reduction is lower (Carstens & Moberg, 2000). We therefore hypothesise:

H4: Error perceptions will negatively influence health distress reduction.

3.3. *Effects of error processing on attitude formation and usage intention*

Risk perceptions are a powerful predictor of consumers' behaviours, attitudes, and their motivation to avoid mistakes. They substantially influence individuals' information adoption and purchase decisions (Nicolaou & McKnight, 2006; Pavlou & Gefen, 2004). Since user behaviour varies subject to individual risk perceptions, segmentation by risk perception is an effective strategy to predict consumer attitudes and intentions towards specific products or services. For instance, higher user risk perceptions negatively influence attitudes towards internet shopping, online purchasing, and mobile banking services (Luo et al., 2010). In healthcare contexts, where risk perceptions often relate to beliefs on vulnerability to a disease, they are a significant predictor of self-protective behaviour (Schwarzer, 2008). According to the health belief model (Janz & Becker, 1984) and protective motivation theory (Rogers, 1983), risk perceptions significantly predict individuals' likelihood of taking preventive action. For health campaigns, the perceived risk of catching a disease motivates attitude formation (Rimal, 2001). Research into health behaviours suggests that individuals with high-risk perceptions have more negative attitudes and fewer intentions to use health IT (Hsieh, 2015). Based on these findings, we hypothesise:

H5: Risk perception will negatively influence attitude formation towards health wearables.

Previous studies have investigated how self-efficacy affects decision-making and behaviours (Bandura, 1993; Johnston & Warkentin, 2010). IS research suggests that individuals with high computer self-efficacy are more likely to develop positive attitudes and have higher technology usage intentions in general (Boss et al., 2015; Lam & Lee, 2006), as well as in the field of mHealth app adopt (Balapour et al., 2019). In healthcare, self-efficacy is a crucial determinant of individuals' health-protective intentions and behaviours (Rahman et al., 2016; Schwarzer, 2014). Perceived self-efficacy and negative emotions also determine individuals' information-seeking behaviours (S. Y. Lee et al., 2008). Since perceived self-efficacy involves subjective beliefs in one's ability to perform a desired behaviour, these subjective beliefs reflect individuals' perceived capabilities to use health wearables to accomplish health-related tasks. Self-efficacy affects information usage intensity in the context of heart diseases and increases individuals' confidence to conduct breast cancer examinations (Rimal, 2001). Moreover, research confirms that attitude formation towards self-care is directly associated with higher self-efficacy (Walker et al., 2015). Following this, if self-efficacy increases, then attitude formation towards the object of these beliefs will also increase. Thus, we hypothesise:

H6: Self-efficacy will positively influence attitude formation towards health wearables.

Research in various disciplines, such as politics, communication, psychology or healthcare, considers threats a particularly relevant source of attitude formation and action (Neuberg et al., 2011). When threats are perceived, individuals adjust their behaviour subject to the extent of damage they perceive to be associated with the threats. Transferred to the health context, if individuals perceive a threat to their health status, they assess the benefits and barriers to a recommended health action and change their attitudes accordingly. Physicians' threat perceptions have a negative impact on their attitudes to use health IT (Bhattacherjee & Hikmet, 2007). We follow this line of thought for the context of individuals and hold that:

H7: Threat perception will negatively influence attitude formation towards health wearables.

The adverse effects of stress on individuals' behaviours and attitudes are well-known from other fields (Ragu-Nathan et al., 2008). For instance, owing to the negative correlation between occupational stressors and attitudes to change, very stressed individuals demonstrate decreased commitment and increased reluctance to accept organisational change interventions (Vakola & Nikolaou, 2005). Individuals who experience stress in their profession show poor attitudes towards their organisations and are more likely to resign. Health distress, covering the hidden emotional burdens, stresses, and worries associated with managing diseases, has been analysed as a determinant of user attitudes towards IT (Ahuja & Thatcher, 2005). We expect that, in individuals' minds, a higher potential for a distress reduction owing to health wearables' benefits will be connected to a more positive attitude towards health wearables. Thus, we hypothesise:

H8: Health distress reduction will positively influence attitude formation towards health wearables.

It is well-documented that attitudes influence behaviour by affecting behavioural intentions (Kroenung & Eckhardt, 2015; Pavlou & Gefen, 2004). Adoption studies for health IT and ELM studies confirm the positive relationship between attitude formation and usage intentions (Angst & Agarwal, 2009). Also, many technology acceptance studies show that attitude towards IT influences the intention to use it (Venkatesh et al., 2012). We hypothesise:

H9: Attitude formation towards health wearables will positively influence intentions to use health wearables.

4. Methodology

4.1. Procedure and participants

We conducted an online survey targeted towards people with diabetes, for whom digital self-monitoring of their health status is an integral part of their chronic disease management, and potential diagnostic device errors can have severe consequences. After requesting basic details on sociodemographics and health status, participants watched a two-minute video explaining the functionality and use of actual health wearables. We used a non-invasive self-monitor watch that measures glucose levels through the skin without cumbersome and painful blood-based tests with a simple press gesture on the digital device. To ensure that participants completed the survey with a shared understanding, they received three test questions on the health wearables' purpose of usage, which they needed to answer to continue the survey.

Diabetes is a long-term metabolic pathological condition in which the blood glucose level fluctuates outside the individual normoglycemic range (often between 90 to 120 mg/dL). We implemented two error types and potential consequences thereof (Breton & Kovatchev, 2010; Rodbard, 2016). In detail, detecting an abnormal blood glucose level, although the de facto level is within the recommended limit (false-positive error), can induce over-cautiousness and lead to additional stress owing to an alarming diagnosis and potentially unnecessary physician visits. On the other hand, a failure to detect abnormal blood glucose levels (false-negative error) can lead to both hyperglycaemia (high blood glucose levels) and hypoglycaemia (low blood glucose levels). We use a three-group between-design (Table 1) with a health wearable without any error and two treatments that included a 30% chance for either a false-positive or a false-negative error (Takacs et al., 2014) (Appendix A).

We piloted the survey with four faculty members, eight doctoral students, and nine non-scientific respondents from different fields to ensure that the instructions and the wording of the questionnaire items were easy to understand and unambiguous. We made minor changes to the survey instructions and certain items' wording. A market research company with substantial experience in this field administered the final sample.

Table 1. Potential diagnostic outcomes and study design.

Potential Diagnostic Outcomes		Glucose level (reported): *within the normoglycemic range*	Glucose level (reported): *below or above the normoglycemic range*
Glucose level (de-facto)	*within the normoglycemic range*	**Baseline**: No error	**Treatment 1**: False-positive error
	below or above the normoglycemic range	**Treatment 2** False-negative error	**Baseline**: No Error

4.2. Operationalization of constructs

We used validated measures from prior studies to operationalise our constructs and adapted these to the context of health wearables. We used multi-item scales since they provide better predictive validity for construct measurement than single-item-constructs (Diamantopoulos et al., 2012). In this research context, these constructs apply to individuals who are affected by an omnipresent disease, e.g. diabetes, and can profit from health wearables to manage their health better. We measured the effects of individuals' error perceptions by adopting the reliability construct from McKnight et al. (2011). Since self-efficacy and distress are fairly broad constructs and are used in various health and IS contexts (Schwarzer, 2014), we used specific health self-efficacy (Lorig et al., 1999) and distress scales (Lorig et al., 1996). We adapted these to the focal context of diabetes. We measured perceived threat using the items of Bala and Venkatesh (2015), who adapted Major et al. (1998) threat perception scale to the IS context. We measured risk perception with a scale adapted from Stone and Grønhaug (1993), with financial, performance, physical, and psychological loss components and an additional item for health risks concerning diabetes. For attitude formation, we followed Dinev et al. (2016). Our usage intention items are based on the ELM study on IT acceptance by Bhattacherjee and Sanford (2006). Besides the demographic variables age and gender, we also controlled for the pre-attitude concerning blood glucose metres (Polonsky et al., 2015), individuals' health status (Lorig et al., 1996), expertise about health wearables (H. S. Bansal & Voyer, 2000), and individuals' trusting stances (McKnight et al., 2002). Appendix B provides an overview of all questionnaire items.

4.3. Measurement validity

To account for potential common method bias, we implemented the procedural remedies recommended by Podsakoff et al. (2003), such as providing contextual information and definitions to reduce ambiguity. Given the sensitivity of health information, we guaranteed respondent anonymity and ensured that their data was used only for scientific, non-commercial purposes. Harman's single-factor test indicated that no factor explained more than 50% of the total co-variance among the measures (43.1% for the most vital influence factor). In addition, we followed Kock (2015) to assess all factor-level variance inflation factors (VIF) to test for common method bias. All values were below the recommended threshold of

Table 2. Interconstruct correlation matrix.

	Mean	s.d.	AGE	ATT	EPR	EXP	GEN	DDR	HEA	ITU	RSK	PRE	SEF	THR	TRU
AGE	54.58	11.81	1.00												
ATT	5.06	1.91	−0.09	0.97											
EPR	3.96	1.66	0.01	−0.63	0.92										
EXP	3.85	1.92	−0.18	0.16	−0.20	0.95									
GEN	1.39	0.49	−0.34	0.01	0.04	0.02	1.00								
DDR	3.91	1.95	0.00	0.47	−0.44	0.14	−0.01	0.93							
HEA	4.23	1.55	−0.15	0.10	−0.06	0.21	0.01	0.13	1.00						
ITU	4.68	2.12	−0.15	0.87	−0.54	0.20	0.06	0.47	0.12	0.99					
RSK	2.83	1.51	−0.09	−0.47	0.49	−0.04	0.19	−0.21	−0.01	−0.36	0.80				
PRE	5.04	1.39	0.01	0.16	−0.25	0.42	−0.03	0.29	0.20	0.20	−0.18	0.82			
SEF	3.99	1.65	−0.07	0.65	−0.67	0.31	−0.03	0.54	0.13	0.61	−0.36	0.32	0.89		
THR	1.90	1.44	0.07	−0.26	0.07	0.18	0.13	−0.10	0.04	−0.24	0.29	0.07	−0.11	0.91	
TRU	4.26	1.33	−0.02	0.13	−0.05	0.26	−0.13	0.11	−0.02	0.21	−0.01	0.08	0.23	0.03	0.84

3.3, indicating the common method bias did not seem to have affected the data. For our data analysis, we used SmartPLS (Ringle et al., 2014), owing to its suitability to help 'understand the variation in the dependent variables that are explained by the dependent variables' (Petter, 2018). While we succeeded in obtaining a clean sample of 193 actual people with diabetes, we cannot assume representativeness or fulfilment of the distribution requirements of co-variance-based structural equation modelling techniques. Concerning internal consistency reliability, all Cronbach's alphas were higher than 0.7. To assess the reflective constructs' convergent validity, we analysed the indicators' reliability and each construct's average variance extracted (AVE), which was above 0.5 for all cases (Appendix B). We assessed indicator reliability by examining the outer loadings of each item on its construct. All item loadings exceeded the suggested threshold of 0.708, indicating adequate reliability (Chin et al., 2003). Values for composite reliabilities of constructs with multiple indicators exceeded the recommended threshold of 0.7. We assessed discriminant validity by analysing the cross-loadings, confirming that all factor loadings were higher than any cross-loadings. The AVE for all constructs was higher than the recommended threshold of 0.5. Further, the Fornell-Larcker criterion was validated, since the square roots of each construct's AVE were higher than the correlations with all other constructs in the model (Table 2). Finally, considering the heterotrait-monotrait ratio of correlations (HTMT), all correlations were below the recommended threshold of 0.9. Thus, we obtained overall support for discriminant validity.

5. Results

5.1. Descriptive statistics and controls

One hundred ninety-three participants completed the survey, of which 118 were male and 75 were female. Sixty-eight participants had diabetes Type 1, and 125 had Type 2; all of them were on intensive insulin therapy (Table 3). All participants required regular self-monitoring of blood glucose, thus sharing a potentially high involvement in the study's subject matter. More than three out of four participants (76.1 %) had to consult a physician about their diabetes at least every two months. Furthermore, a comparably

Table 3. Demographic profile of respondents.

Demographic characteristic	Frequency	Percentage
Male	118	61.1
Female	75	38.9
Age		
19 or less	1	0.5
20–29	7	3.6
30–39	15	7.8
40–49	31	16.1
50–59	67	34.7
60–69	59	30.6
70–79	13	6.7
Education:		
Secondary school	121	62.7
High school diploma	26	13.5
College degree	43	22.3
PhD degree	3	1.6
Diabetes type:		
Type 1	68	35.2
Type 2 (on intensive insulin therapy)	125	64.8
Frequency of diabetes related physician consultation		
Every month	12	6.2
Every 1–2 months	135	69.9
Every 3–6 months	40	20.7
Every 7–12 months	4	2.1
Less than 1× per year	2	1.0
Time since diabetes was first diagnosed		
Less than 5 years	24	12.4
5–9 years	43	22.2
10–19 years	67	34.7
20–29 years	38	19.7
30–39 years	10	5.2
40 or more years	11	5.7

large number of 57 participants gave us voluntary feedback, mostly appreciating our work and highlighting its relevance to them. This high ratio of voluntary feed increased our confidence in the respondents' motivation.

5.2. Structural model and hypotheses tests

We used PLS analysis to verify our structural model and to test the hypotheses. To assess potential collinearity, we analysed the exogenous constructs' variance inflation factors (VIF). All values were lower than 1.5 and thus well below the recommended threshold of 3.3. The overall variance explained was 51.6% for attitude formation and 78.4% for intentions to use. This suggests that our theoretical model explains a substantial share of the overall variance in the primary outcome variables. We conducted the bootstrap procedure with 300 subsamples and 5,000 iterations to determine the significance of the different path estimates. Figure 2 presents an overview of the effect sizes and their statistical significance.

Concerning the effects of individuals' error perceptions on the central route, as hypothesised, error perception had a significant positive effect on individuals' risk perceptions ($p < 0.001$), supporting H1, as well as a significant negative effect on perceived self-efficacy ($p < 0.001$), supporting H2. The effects of error perceptions on the peripheral route were less pronounced, leading to a significantly negative effect on health distress reduction ($p <$

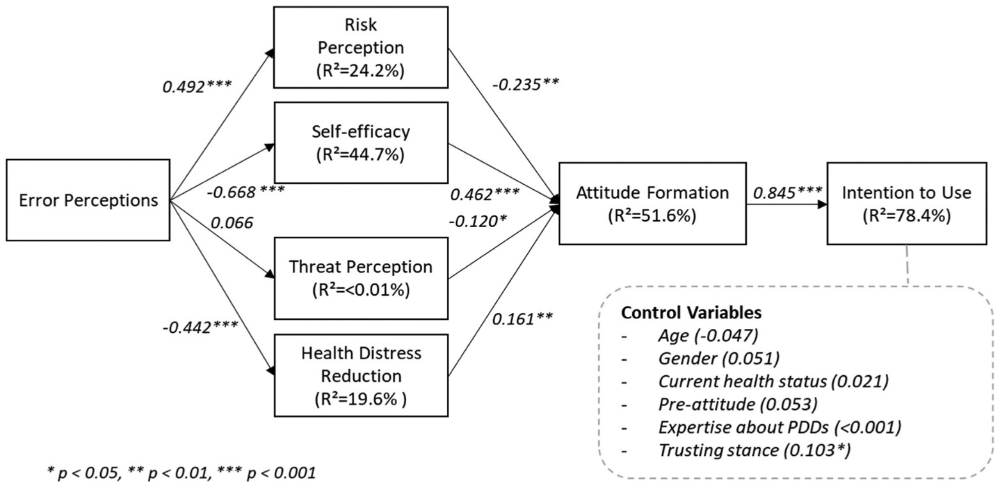

Figure 2. Research model results.

0.001). Still, there was no significant influence on threat perception ($p > 0.05$). Thus, we obtained support for H4 but rejected H3. We then analysed the effects of the central and the peripheral route cues on individuals' attitude formation. Both central route cues, risk perception, and self-efficacy significantly influence attitude formation towards health wearables. The significant negative effect of risk perceptions on attitude formation ($p < 0.01$) provided support for H5, while the significant positive effect of self-efficacy on attitude formation ($p < 0.001$) provided support for H6. For the peripheral route, threat perception and health distress reduction had significant albeit less pronounced influences on attitude formation towards health wearables. For health distress reduction, the relationship was significant at the 1% significance level, providing support for H8, while for threat perception, we obtained significance at the 5% level, providing support for H7. As hypothesised, attitude formation had strong and significantly positive effects on intentions to use ($p < 0.001$), supporting H9. An overview of the hypotheses tests is reported in Table 4.

6. Discussion and implications

6.1. Discussion

Our research was motivated by the increasing reliance on IT, the significant consequences of IT errors on individuals in particular fields such as health IT, and the lack of knowledge on the perceptual and behavioural effects of IT errors on individuals. Using the example of people with diabetes, we sought to close existing research gaps by uncovering how individuals perceive, process, and respond to diagnostic device errors. Drawing upon the ELM, we found that perceptions of diagnostic device errors are processed along central and peripheral routes. Still, the former have a much stronger influence on individuals' attitude formation and usage intentions. These findings will now be discussed.

Considering dual process models, we found that individuals primarily process diagnostic device errors using central cues, involving self-efficacy and perceived risk, and to

Table 4. Results by hypothesis.

Hypothesis	Support?
H1: Error perceptions -> Risk perception	Yes
H2: Error perceptions -> Self-efficacy	Yes
H3: Error perceptions -> Threat perception	No
H4: Error perceptions -> Health distress reduction	Yes
H5: Risk perception -> Attitude formation towards health wearables	Yes
H6: Self-Efficacy -> Attitude formation towards health wearables	Yes
H7: Threat perception -> Attitude formation towards health wearables	Yes
H8: Health distress reduction -> Attitudes formation towards health wearables	Yes
H9: Attitude formation towards health wearables -> Intentions to use health wearables	Yes

a lesser extent, through a potential reduction of health distress as a peripheral cue. These results align with other ELM studies that found attitude formation is simultaneously influenced by a continuum of both peripheral and central cues (G. Bansal et al., 2015; Bhattacherjee & Sanford, 2006). The uncertainty about novel technologies and their functioning can reinforce dual-route processing (Angst & Agarwal, 2009; Tormala, 2016). However, while uncertainty generally stimulates dual-route processing, central processes often predominate. Individuals engage in deeper and more thoughtful information processing when they feel uncertain, stimulating involvement and, therefore, central information processing (Petrocelli et al., 2007). We interpret that individuals processed diagnostic device errors primarily using central cues: diagnostic device errors lead to uncertainty and produce a desire for certainty, leading individuals to process available information more deeply and thoughtfully (central route) (Tormala, 2016).

Our results also show that both routes influence individuals' behavioural responses in determining their attitude formation towards health wearables. The specific route used to enable attitude formation is critical because central route attitude formation tends to have different consequences and properties than peripheral route attitude formation (Petty & Cacioppo, 1986). Several studies provide evidence that attitudes resulting from more effortful thinking better predict behavioural intentions and guide actions than attitudes resulting from little thinking (Barden & Tormala, 2014). Since we found central cues, i.e. risk perception and self-efficacy, to be dominant, and since attitudes that result from central route processes tend to be stronger than those from peripheral route processes, attitudes concerning diagnostic device errors are likely to be more persistent and resistant over time when challenged by contrary information. In addition, strong attitudes guide thinking and, perhaps most importantly, behaviour (Ajzen & Fishbein, 2000). This means that health wearables with few diagnostic device errors could eventually lead to strongly positive attitudes towards health wearables. If these attitudes towards health wearables persist in individuals' memory, they are more likely to continue to influence behaviour over time than weak attitudes, leading to higher intentions to use (Sheeran et al., 2013; Strack & Deutsch, 2004). These are essential insights regarding initial technology adoption decisions and algorithm aversion (Daschner & Obermaier, 2022; Weiler et al., 2022).

Concerning the individual constructs on both routes, we found that individuals carefully scrutinise and evaluate diagnostic device errors using self-efficacy and risk perception. These effects are in line with previous IS and health studies (Boss et al., 2015; Breton & Kovatchev, 2010; Ong et al., 2014). First, perceived self-efficacy is a crucial determinant of individuals' attitudes to technology, continuance, and switching decisions (Rahman et al., 2016). Given the importance of health to everyone, individuals may be more reluctant when doubting the reliability of IT as a potential risk to their health. In line with previous research that has demonstrated the adverse effects of risk perceptions on attitudes (Luo et al., 2010), our results support this relationship for health wearables and contribute to other research on risk perceptions and decision-making (Nicolaou & McKnight, 2006; Nicolaou et al., 2013; Park et al., 2015) by uncovering that error perceptions function as an antecedent of individuals' risk perceptions. We further obtained support for the effects of error perceptions on individuals' health distress reduction, but we need to note that their threat perceptions were not affected. Concerning health distress reduction, our results align with self-regulation models (Leventhal et al., 2003). Studies on technostress, i.e. the negative stress of end users owing to the introduction of new technologies (Mahapatra & Pillai, 2018), demonstrate the notable effects of both acute (Ragu-Nathan et al., 2008) and chronic (Riedl et al., 2012) technology stressors on physiological parameters, which in turn have been shown to have the potential to affect health considerably (Ragu-Nathan et al., 2008). For individuals, bodily symptoms from distress may intermingle with symptoms from physical illness, increasing the experience of poor health. Thus, the unexpected experience of diagnostic device errors can create health distress and direct their attention inward towards bodily processes (Gonzalez et al., 2011), which block conceptual, rational considerations of effective coping and can result in negative attitudes towards health wearables. Concerning individuals' threat perceptions, at first glance, it might seem counter-intuitive that error perceptions do not significantly affect threat perception. However, our interpretation is that, when considering health wearables, individuals evaluate the long-term use of health wearables and, therefore, consider the consequences over several years (Davey et al., 2012). In contrast to rather easy or short-term decisions, such as subliminal classical conditioning that occurs outside of awareness, important life decisions require more careful consideration and are therefore processed along the central route. Thus, the occurring peripheral threat cues considering diagnostic device errors could be outweighed by other more conscious and more rational central processing factors.

6.2. Implications for theory

The empirical results of our study revealed three key findings, each of which contributes to theory. We uncovered the underlying mechanisms of the perceptions and processing of diagnostic device errors along central and peripheral cues and their attitude formation and usage intentions concerning health wearables. Using an ELM-based dual information process model instead of IT acceptance models, we uncovered the influences of diagnostic device errors on attitudes to erroneous health IT. Thus, we complement prior IT acceptance theories by emphasising that IT acceptance should be preceded and framed by informational contexts around the technology in question. At the same time, we obtained rich insights and supported the growing research streams of dual process models of health behaviours (Hagger, 2016; Sheeran et al., 2013).

The identified non-significant influences of error perception on perceived threats are a contribution rather than a limitation. On the one hand, studies in cognitive psychology show that peripheral cues significantly impact cognition (central cues) (Forgas, 2002). On the other hand, IS and neuropsychology uncovered that central higher-order processes can regulate amygdala-mediated peripheral processes (Riedl et al., 2012). We followed the second research stream and argued that peripheral threat cues could be regulated in individuals' minds by central higher-order processes of conscious rational calculation of the likelihood of losses (e.g. risk perception). Such central regulation may also occur in other technology contexts where individuals are highly involved because they depend on such technologies (i.e. online banking). Since these individuals are often experienced and trained in their usage over time, this often makes them more confident in their cognitive thinking, and peripheral cues, such as emotions or affect, might be outweighed and have less influence on individuals' decision-making. Thus, this adds value to health IS research since this circumstance is possibly a result of the interplays of central and peripheral cues and warrants further investigations for all dual process models. This has important implications, e.g. for research addressing interface design to enable users to detect errors better (Braun et al., 2023).

The literature on ELM and health care has not sufficiently considered negative variables besides privacy concerns. Thus, we responded to the calls from Angst and Agarwal (2009) and Dinev et al. (2015), who requested extending ELM research with new variables that could negatively influence attitudes. Our study deepens the understanding of attitude formation by aligning it with negative functional aspects of technologies in the context of sensitive data. Focusing on the error perceptions of a specific healthcare technology, we shed light on individuals' expectations on technologies' freedom from error and their behavioural responses in the form of attitudes and intentions. This is especially relevant since IT increasingly assists us in our daily lives and creates dependencies on its accurate functioning (Gupta et al., 2023; Matt, 2022). Researchers should take the opportunity to analyse individuals' perceptions of diagnostic device errors in the context of other health technologies and measure potential effects on attitude formations and usage over time. Such analyses seem especially beneficial for scenarios where individuals may be obliged to continue using health IT or any other form of IT that may be prone to specific errors. For instance, although the professional healthcare sector is subject to strict regulations in many countries, patients must still trust hospital operators to choose current and accurate healthcare technologies.

In contrast, for people with diabetes, the medical task of self-monitoring blood glucose can be seen as a regular requirement to ensure their health. Still, the selection of health wearables is their choice, and dependent on the country, it may not be protected by such strict regulations. Although the healthcare context provides a fertile setting, future research could also explore the interplay of diagnostic device errors, error perceptions, and attitude formations in other contexts with a strongly increasing availability of data (Abdolkhani et al., 2023) but critical outcomes for users, e.g. for decision support in financial contexts (Mollá et al., 2022).

Beyond the context of health wearables, our work adds to the literature on perceived risk as a factor in the adoption of new technologies in healthcare (Schnall et al., 2015). We considered a scenario in which the use of IT can lead to both a significant increase in quality of life (through easier use), but also to threatening consequences in the event of errors. This is undoubtedly not representative of the assessments of perceived risk in other IT applications (such as the risk associated with data disclosure), but it reflects the increasing functionality and use of AI in ever more sensitive areas of everyday life very well. Our work therefore enriches current discussions in the context of artificial intelligence in the healthcare sector. These include, for instance, AI-based risk considerations and trust (Gupta et al., 2023; Solberg et al., 2022), the adoption of smart devices subject to functional requirements (Im et al., 2022) as well as recent debates on AI explainability in the medical field (Liu et al., 2022). We recommend that future research in the latter field integrates our findings and puts a stronger emphasis on finding suitable means to communicate medical AI functionality along with information on potential errors and their consequences for users. This is all the more important as these added functionalities ultimately have a strong influence on the possibilities for individuals to gain control over their own state of health and how they deal with illnesses.

6.3. Implications for practice

Our empirical results have substantial value for practice, which is mainly based on an improved understanding of how individuals deal with technology-related threats that result from the usage of health IT. For suppliers, while erroneous IT is generally seen as troublesome for users, false information from health wearables can pose significant health risks to individuals. Our results have shown that diagnostic device errors translate into users' error perceptions, enabling elaboration likelihoods, and affecting their attitude formation towards health wearables, and, eventually their usage intentions. While in most cases, it can be assumed that device manufacturers do not intend to integrate errors, ensuring higher levels of freedom from error often requires more research or better components, which usually results in higher costs. Thus, suppliers must match their customers' expectations concerning their products' freedom from error with accruing development and manufacturing costs. To establish consumer trust, they may resort to external sources of credibility (such as test facilities or certificates), which may be particularly helpful for new products or relatively unknown suppliers (McKnight et al., 2011).

Another contribution is the finding that a strong focus on user attitude formation as a proxy to measure the success of marketing campaigns, for instance, can be insufficient since it is vital to know how users' attitudes are formed. Our model provides a more profound basis for tracking attitude formations and the different causes attributable to central and peripheral route factors. Concerning diagnostic device errors, communication strategies or health campaigns that address these errors should seek to activate the central route by stimulating the factors of self-efficacy and risk perception, as well as sending messages targeting health distress reduction on the peripheral route. For instance, suppliers who seek to build error-free devices can emphasise the high accuracy of their devices in their advertising and can stress the suitability to conduct glucose measurements with little worry. This will directly address the peripheral route, particularly health distress reduction, and users will probably develop more positive attitudes towards their products.

Finally, for the communication of diagnostic device errors to individuals, we advise suppliers, public health institutions, and regulators to carefully frame information based on de facto diagnostic device errors because individuals' error perceptions strongly affect central and peripheral processes on attitude formations and usage intentions. This topic is also of high current relevance in the context of the European General Data Protection Regulation (GDPR), which seeks to enforce more transparency regarding data storage, data usage, and data accuracy (European Commission of Justice and Consumers, 2018). These aspects become more relevant not only because health IT is often interconnected and can automatically collect, process, and disseminate information to different entities but also becomes more relevant given the rising capabilities of AI, which are often difficult to control by both providers and users, which raises new questions of responsibility (Lüthi et al., 2023). In a more connected world of digital health, individuals' decisions to adopt a certain device with a specific diagnostic device error level may constitute a single source of error that can also affect more complex processes in which other entities or more powerful devices and algorithms are involved. The expected increase of interconnected information-sharing networks in healthcare highlights the necessity to conduct more research into error processing, considering erroneous personal health information. Suppose ancillary conditions and privacy configurations meet patients' requirements. In that case, automatic dissemination of diagnostic data may deliver additional information for research and drug development, may reduce public healthcare system costs, and may eventually help many people to improve their health conditions.

7. Research limitations and future work

Despite utmost care, this study has limitations. First, for methodological reasons, we could only consider one specific type of health wearables. We acknowledge that individual device or supplier characteristics (such as voice-command features, a compelling design, materials of high-value appearance, impacts of brand names, and individuals' relationships with suppliers) could impact associated risk perceptions (Weith & Matt, 2023). Thus, we recommend the use of other types of health wearables in future studies to examine potential differences in individuals' perceptions across devices and over time since risk perceptions may change over time and may be subject to external influences, such as recent news on hacker attacks on a supplier (Angst & Agarwal, 2009).

Second, owing to the currently limited availability of health wearables in the market, instead of de facto behaviour, we could only assess diabetics' intentions to use health wearables. Despite the frequent use of intentions as a predictor of de facto behaviour, individuals may still behave differently than they have indicated. We chose a developing technology for our study because novel technologies are often more prone to device errors and might create a more credible scenario. Furthermore, conducting such research at an early stage opens new opportunities to help shape these technologies before they have reached actual market diffusion. The high involvement of our participants, as can be seen in the extensive voluntary feedback and support we received, highlights the pressing need to answer such questions now. Importantly, once health wearables have achieved market diffusion, studies should focus on how these devices affect self-diagnosis behaviours (Aboueid et al., 2019; Shahsavar & Choudhury, 2023).

Third, our results apply to people with Type 1 and Type 2 diabetes who need insulin therapy and who may thus show different patterns compared to users with lower involvement. Decisions of highly involved individuals, who rely more on the central route, are claimed to be more sustainable than the decisions of less involved individuals, based on the peripheral route (G. Bansal et al., 2015). Furthermore, our sample included participants from one European country, meaning we cannot assume that our results represent other countries, especially those that differ significantly in market maturity (Tuzovic et al., 2017). Also, individuals' access to health wearables and their decisions to consult physicians are likely to be a factor in the general healthcare quality levels and the availability of physicians, emphasising the potential for health wearables to improve healthcare and enable new digital healthcare services that may have particular benefits for rural areas and less developed countries (Barrett et al., 2015). Therefore, we recommend replications with different samples in different countries and long-term analyses on the persistence of the effects over time and subject to stimuli that affect involvement, privacy concerns (Sui et al., 2023), and attitudes.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendices

Appendix A. Scenarios

Group	Treatment
No error	 With the new biosensor system, the blood glucose level is measured via skin resistance. This measurement is almost error-free.
False-positive error	 With the new biosensor system, the blood glucose level is measured via skin resistance. Unfortunately, in 3 out of 10 cases, the value shown is too high or too low, although the blood glucose level is within a normal range.
False-negative error	 With the new biosensor system, the blood glucose level is measured via skin resistance. Unfortunately, in 3 out of 10 cases, the value shown indicates a normal range, although the true value is either too high or too low.

Source: PKvitality.com

Appendix B. Measurement Items

Items	Measures
	Error Perceptions (EPR): Users' error perception towards health wearables.
	Composite reliability = 0.98 AVE = 0.95 1 = *strongly disagree* to 7 = *strongly agree*
EPR1	Health wearables are a very reliable technology
EPR2	Health wearables doesn't disappoint me
EPR3	Health wearables are very dependable
EPR4	In my view, health wearables do not fail
	Self-efficacy (SEF): Users' confidence in managing diabetes and its effects using wearables.
	Composite reliability = 0.96 AVE = 0.79 1 = *very uncertain* to 7 = *very certain*
	When using health wearables, how sure are you that . . .
SEF1	. . . fatigue caused by your diabetes doesn't restrict you in the things you want to do
SEF2	. . . the physical complaints caused by your diabetes don't restrict you in the things you want to do
SEF3	. . . the emotional stress caused by your diabetes disease doesn't restrict you in the things you want to do
SEF4	. . . other symptoms or health problems caused by your diabetes disease don't restrict you in the things you want to do
SEF5	. . . you can perform tasks to manage your health status so that you need to go to the doctor less often
SEF6	. . . you can take other measures (e.g. take pills) to reduce the extent of your diabetes on your daily life
	Risk perception (RSK): Perceived concerns about health wearables' cost, functionality, and physical burden.
	Composite reliability = 0.90 AVE = 0.65 1 = *strongly disagree* to 7 = *strongly agree*
	I fear that a health wearable . . .
RSK1	. . . is not worth the money
RSK2	. . . won't work correctly
RSK3	. . . will physically burden me
	Health distress reduction (HDR): Perceived impact of health wearables on emotional well-being.
	Composite reliability = 0.96 AVE = 0.87 1 = *strongly disagree* to 7 = *strongly agree*
	Through the use of a health wearable, I would be . . .
HDR1	. . . more courageous regarding my disease
HDR2	. . . less afraid regarding the future development of my disease
HDR3	. . . less worried about my current health status
HDR4	. . . less frustrated because of my restrictions
	Threat perception (THR): Emotional perceptions regarding fear, concerns, pressure, and stress.
	Composite reliability = 0.95 AVE = 0.83 1 = *strongly disagree* to 7 = *strongly agree*
	When I think about the use of a health wearable, I . . .
THR1	. . . am scared
THR2	. . . have concerns
THR3	. . . feel pressurized
THR4	. . . feel stressed
	Attitude formation towards health wearables (ATT): Overall attitude towards health wearables regarding their value and desirability.
	Composite reliability = 0.98 AVE = 0.95 1 = *strongly disagree* to 7 = *strongly agree*
ATT1	I think that having this health wearable is a good idea
ATT2	I think that using this health wearable is a good idea
ATT3	I have a positive opinion about this health wearable
	Intention to use health wearables (ITU): Intended willingness to use health wearables in the near future.
	Composite reliability = 0.99 AVE = 0.98 1 = *strongly disagree* to 7 = *strongly agree*
	I would use this health wearable or a similar device . . .
ITU1	. . . in the near future
ITU2	. . . in the near future regularly
ITU3	. . . in the near future to improve my health, productivity, performance, or effectiveness
	Expertise about health wearables (EXP): Self-assessed knowledge and experience regarding health wearables.
	Composite reliability = 0.97 AVE = 0.90 1 = *strongly disagree* to 7 = *strongly agree*
	Regarding new health wearables, I . . .
EXP1	. . . have much knowledge
EXP2	. . . gained a lot of experience
EXP3	. . . am very well informed
EXP4	. . . am an expert

(*Continued*)

Items	Measures
	Pre attitude concerning current device (PRE): Perceived effectiveness and satisfaction with the current blood glucose.
	Composite reliability = 0.89 AVE = 0.67 1 = *strongly disagree* to 7 = *strongly agree*
	My current blood glucose metre helps …
PRE1	… me to be more open to new experiences in my life
PRE2	… my doctor and I to know how much diabetes medication I need to take
PRE3	… me to understand what effects nutrition and physical activity have on me
PRE4	… me to feel more satisfied about how everything around my diabetes is working
	Trusting stance (TRU): Inclination to trust others
	Composite reliability = 0.88 AVE = 0.71 1 = *fully inapplicable* to 7 = *fully applicable*
TRU1	Normally, I trust people until they give me a reason not to trust them
TRU2	When I have doubts, I usually decide in favour of people when I meet them for the first time
TRU3	My typical procedure is to trust new acquaintances until they prove that I shouldn't trust them
	Current health status (HEA): Self-assessment of overall health status.
	Composite reliability = 1.00 AVE = 1.00 1 = *very bad* to 7 = *very good*
HEA	Generally, I think my health status is …