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Research article

Self-efficacy and trust in consumers' use of health-technologies devices for sports

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ABSTRACT

The commercial market for wearable health technology is growing but the value these technologies provide for consumers is debatable, as many technologies lack formal validation and are being abandoned at a high rate. The enabling of self-efficacy mechanisms in the design of health technologies, through the factors identified by self-determination theory and the Technology Acceptance Model, could increase the uptake and continued use of these devices. The aim of this research was to investigate how and why people use wearable health technology, and to evaluate their experiences from the perspective of perceptions of autonomy, safety, information security, information accuracy and willingness for continued use. Forty-eight sport enthusiasts or athletes, age range 18–65 and over, completed an online survey with 46 questions. A statistical analysis that included a Mann-Whitney U Test and a Person's Correlation analysis indicated that participants who were confident in their use of a health technology showed satisfaction with previous uses and a sense of autonomy leading to an overall positive experience. Issues around data and personal information security were identified, aligning with extant literature. Findings suggest that: (i) past experience play a role in people's perception of self-efficacy, (ii) the tracking of activities enables of autonomy and confidence, (iii) autonomy influences personal willingness to use health technologies, (iv) strong interest in personal health technologies motivates sustained engagement, and that (v) reliability and validity of data impacts on confidence in health technologies. A conceptual model is proposed for consideration when designing and evaluating health technologies, based on the factors supporting self-efficacy and trust in health technologies. Further research is required to develop this model with the aim of informing designers and developers about how to translate these factors into design features for the development of more effective personal health technology.

1. Introduction

In the last decade studies on personal health technologies have delivered theoretical frameworks, industry standards, and design strategies mostly focusing on people's uptake of technology and gold metrics for the measurement of body data (Duking et al., 2016; Halson et al., 2016; Piwek et al., 2016; Baron et al., 2017; Peake et al., 2018). People's behaviour and attitudes towards their health and the use of health technology varies widely (Murnane et al., 2015; Lee and Lin, 2016). However, this area has not been explored in detail, particularly in relation to people's perceptions of autonomy, safety, information security, information accuracy and willingness for continued use of personal health technologies. The aim of this research was to investigate how and why people use health technology from the perspective of their perceptions of self-efficacy and trust in the use of health technologies in sports.

The commercial market for consumer technologies for evaluating physical and psychological health, training, emotional awareness, monitoring/assisting sleep quality and assessing cognitive function has increased dramatically in recent years. These health technologies are at various stages of development; some have been independently tested to determine its reliability and validity, but many have not (Peake et al., 2018). Consumer technology is moving beyond basic measurement and telemetry of standard vital signs. Predictive algorithms are now in development, with the inclusion of miniaturized sensors, integrated computing and artificial intelligence. These developments make the

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technology smarter, more personalised, and capable of providing real-time feedback to users (Sawka and Friedl, 2018).

A snapshot review of various technologies for health and sports performance revealed that the value of some technologies currently available for consumer use is debatable (Peake et al., 2018). The review identified two key limiting factors to the value of such technologies: only 5% of the technologies reviewed had been formally validated (at the time of publication); and that only a small proportion (10%) of the technologies had been developed for, or used in research, rather than for consumer use. It was recommended that, to ensure the success of their products, companies producing health and performance technologies should consult with consumers to identify real-world need and invest in research to prove the effectiveness of their products. On this point, the current literature states that:

- Individuals engage more with health technology devices if they are involved in activities that meet the core psychological needs of autonomy, relatedness, and competence (Bandura, 2006; Sundar et al., 2012; Chang et al., 2016; Kerner and Goodyear, 2017; Molina and Sundar, 2020).
- Physically active people have a stronger awareness and interest in their personal health, leading them to engage more with such technology (Rupp et al., 2018).
- Perceived motivational properties and technology usability are indicative of user's trust and their intention to adopt wearable technology devices (Rupp et al., 2016, 2018; Beldad and Hegner, 2018)
- User confidence in a health technology is dependent on the validity and reliability of its data, as well as the usefulness of its features for attaining their fitness goals (Davis, 1989; Marangunic and Granic, 2015; Rupp et al., 2016; Beldad and Hegner, 2018)
- Engagement with health technology devices may also depend on the persona profile of individuals and personal factors such as motivation, achievement, and self-regulation (Nicholas et al., 2015; Burns et al., 2020)

For those consumers who abandon the use health technologies within a relatively short period of time following purchase, the literature indicates that the most common cause is that they have given up on their personal health goals, and hence, no longer need the health technology (Murnane et al., 2015; Lee and Lin, 2016). One important determinant of people's personal health choices and solutions is that of self-efficacy, which refers to a person's belief in his or her own agency to influence and make a change in their lives. Therefore, when designing self-health technologies, designers should not overlook features and functions in their technology that enable a person's choice and agency, and support people's decision-making processes about their health (Bandura, 2006).

Studies on people's use of health tech devices and wearable technologies have identified: (i) a need for input from end-users about the effectiveness and value of such technologies for users (Peake et al., 2018), and (ii) a need to enhance people's perception of the reliability and usability of these technologies (Piwek et al., 2016). The enabling of self-efficacy mechanisms in the design of health technologies could increase the uptake and continued use of these devices. The concept of self-efficacy is related to motivation, achievement, and self-regulation (Bandura, 2010), and it is determined by positive experiences.

This article reports a study that investigated the factors supporting sports enthusiasts' motivation and engagement with health-tech devices. This study addressed the following research question: What factors enable self-efficacy and trust in the use of health technologies in sports? The study addresses a gap in the literature that calls for end-users' input about factors influencing their perception of the value of their health tech devices to promote continued use of future technologies. The following sections presents a discussion of key concepts found in the literature about self- efficacy and use of health technologies, the use of a survey methodology and its procedures, the survey results and data analysis. Finally, section 5 introduces a discussion and limitations of findings and a conceptual model of the factors that influencing self-efficacy and engagement with health technologies.

2. Identified factors influencing use of health technologies

The literature on wearable technologies reveals that perceived motivational properties and technology usability are indicative of user's trust and their intention to adopt wearable technology devices. For example, Rupp et al. (2016, 2018) investigated perceived trust and motivation as predictors of continued use of wearable fitness technologies. Trust in commercial companies prompts focus on the potential offered by a technology, rather than its threats. Such trust also contributes to the perceived usefulness of a technology, which significantly influences a user's willingness to continue use (Beldad and Hegner, 2018). Trust in a technology is supported by factors such as how well the device protects the user's information (Chang et al., 2016; Rupp et al., 2016), how valid and reliable its information is, and how clearly it presents this information to the user (Rupp et al., 2016). A systematic review of the validity and reliability studies of Fitbit and ™Jawbone devices revealed conflicting results in the literature and demonstrates a need for further research in this area (Evenson et al., 2015). Similarly, Peake et al. (2018) highlighted the scarcity of this type of research and recommended that manufacturers invest in this area by consulting with users to improve the usefulness of their products.

A user's confidence in a health technology is supported or motivated not only by the validity and reliability of its data, but also the usefulness of its features for attaining their fitness goals. The Technology Acceptance Model (TAM) (Davis, 1989) has been widely used in understanding how perceived ease of use and perceived usefulness influences people's willingness to adopt and continue using a technology (Marangunić and Granić, 2015). Perceived ease of use is the degree to which a person believes that using a technology is "free of effort", whereas perceived usefulness is the degree to which a person believes a technology will enhance their performance (Davis, 1989). In the context of fitness devices, Beldad and Hegner (2018) further expanded their research using the TAM and found that social norms can influence a user's willingness to continue to use a technology.

Recent studies on wearable health technologies and health apps (Clawson et al., 2015; Rupp et al., 2016; Kerner and Goodyear, 2017; Rupp et al., 2018) show that tracking and delivering personalised health data is not always sufficient to engage people in a sustainable manner in relation to their health. This has led to investigations into persona profiles or user archetypes, and technology engagement maps—particularly how each type of persona profile uses technologies (Burns et al., 2020; Nicholas et al., 2015). The four persona archetypes describing how people use digital health technology for health goals are: (i) *Tech Reliant*; (ii) *Self Aware*; (iii) *Health Conscious*; and (iv) *Tech Obsessed*. The first archetype, *Tech Reliant*, is a person who is loyal to a technology for a specific use and is a frequent user. The *Self-Aware* archetype is an active person who uses the technology as a motivator. The *Health-Conscious* archetype is a person driven by their health goal, who does not depend on technology, and can easily become bored of using it. The fourth archetype, *Tech Obsessed*, is a person driven by technology, and someone who is data focused. For this archetype, owning the newest technology is more important than their health goal. Each of the persona profiles uses health technology differently over time (Nicholas et al., 2015).

Lack of consideration of the different users' profiles of how people use technologies for health may influence technology abandonment. Studies demonstrate a high rate of abandonment of health technology as a result of abandonment of a health goal with it (Lee and Lin, 2016; Murnane et al., 2015). We argue then that the design of self-health technologies must deliver valid and reliable information and enable self-efficacy mechanisms that support user's decision-making process about their heath (Bandura, 2006).

This goal of this study was to gain insights about the factors that limit or enable self-efficacy and decision-making in sports enthusiasts when using health technology devices.

3. Methodology

As the primary objective of this present study was to identify factors enabling self-efficacy and trust in the use of health technology, a quantitative research approach was chosen and data was collected using an online questionnaire. In this section, the study design and procedures, measures and sample considerations are presented, respectively.

3.1. Study design and procedures

This study used a cross-sectional survey design allowing researchers to record information about self-efficacy and trust developed during the use of health technology among sports enthusiasts and athletes without manipulating the study environment and their behaviour. The main strength of using a cross-sectional survey design is that it is relatively inexpensive and quick to conduct. Furthermore, it allows the researchers to determine and compare the variables including but not limited to age, gender and income at one point in time (Rindfleisch et al., 2008). Despite this strength, one of the primary limitations of the cross-sectional survey design is that it may limit providing information about sequential cause-and-effect relationships of variables. As such, changes in the behaviour of the participants could not be compared or tracked over time.

Following the cross-sectional survey design, the use of an online questionnaire was considered most appropriate method for collecting quantitative data concerning the perceived ease of use, usefulness, intrinsic and extrinsic motivations, and factors supporting the person's trust in using a device for self-monitoring their health. Online questionnaires can have advantages over other, more traditional, quantitative data collection techniques. For example, they are time and cost efficient, and respondents may be more willing to share personal information which they might prefer not to disclosure in a less anonymous setting (Clark, 2005; Vehovar and Manfreda, 2008). In accordance with the Queensland University of Technology (QUT) ethical guidelines, this online questionnaire was conducted during August 2020 with the ethics approval number: 1900000502.

3.2. Measures

An online questionnaire was developed based on the measures from the existing literature on acceptance of wearable technology outlined in Table 1. Survey questions were framed particularly around the self-efficacy scales derived from a study by Bandura (2010). These scales were also applied in later studies to measure wearable technology acceptance, including but not limited to the workplace context (Jacobs et al., 2019). Examples of descriptive questions and measurement items included in this questionnaire were:

- Have you used wearable technology for purposes not related to your sports practice?
- Considering the device with which you have the most experience, what was the quality of your experience?
- Would you voluntarily use wearable technology that tracks your activity or physical status during sports practice, to monitor body status and improve safety from injury?

The questions also included items identified in the literature as valuable predictors of technology acceptance that support the person's trust about the use devices for self-monitoring health, these are: perceived ease of use, usefulness, intrinsic and extrinsic motivation. Demographic data were collected through questions using ranking and open-response formats. These questions provided a picture of the sample participants' sports practice characteristics, their experience when using wearable technology and their opinions toward wearable technology. The questions concerning factors enabling self-efficacy and trust were measured on a Likert scale. These questions and measurement items were developed based on the work of Jacobs et al. (2019) with slight modifications in question wording. For example, *'online information about work processes'* was modified to *'online information about my health around sports practice'*. Such modification was made to ensure the suitability of the measurement items in the context of wearable technology in sport. Subsequently, the validity and reliability of this questionnaire were tested with Exploratory Factor Analysis (EFA) and Cronbach's alpha respectively using the IBM SPSS software. However, it is important to note that an EFA of this present study was merely to summarise and understand extracted factors based on prior knowledge in existing literature without intending to reduce data or factors (Fabrigar et al., 1999; Hair et al., 2010).

For validity, an EFA was conducted using principal axis factoring with an oblique rotation to identify underlying factors in the data. Results indicated a Kaiser-Meyer-Olkin measure of sampling adequacy at .62, above the cut-off of .60, supporting the adequacy of the sample for this study. In addition, Bartlett's Test of Sphericity was found significant ($p =$ .000) suggesting correlations within the data (Hair et al., 2010; Williams et al., 2010). As shown in Table 2, a six-factor structure solution with selected 10 measurement items is presented. An oblique rotation method

Table 1. The measurement items and scale types.

Construct	Code	Item	Measurement type
Perceived Autonomy	PA	I was involved in choosing the wearable technology.	Five-point Likert: 'Not Involved = 1' and 'Extremely Involved = 5'
Perceived Quality of Previous Usage Experience	PQ	The quality of your experience with the wearable technology device was: My experience was:	Five-point Likert: 'Very Bad = 1' and 'Very Good = 5'
Perceived Safety	PS	I was provided adequate information about who would see the data collected from the wearable technology.	Five-point Likert: 'Strongly Disagree = 1' and 'Strongly Agree = 5'
Perceived Information Security	PIS	For data security and privacy, I was: When my data recorded from wearable technology that is not secured and could be accessed by people without permission, I was:	Four-point Likert: 'Not Concerned = 1' and 'Very Concerned = 4'
Perceived Information Accuracy	PIA	I was provided accurate information about what would be measured by the wearable technology (such as movement, location and heart rate).	Five-point Likert: 'Strongly Disagree = 1' and 'Strongly Agree = 5'
Perceived Willingness for Continuous Use	PWCU	I would voluntarily use wearable technology that tracks my activity or physical status during sports practice BUT NOT outside of my sports organisation: to monitor and improve safety from injury.	Five-point Likert: 'Strongly Disagree = 1' and 'Strongly Agree = 5'
		I would voluntarily use wearable technology that tracks my activity or physical status during my sports practice AND in my daily life: to monitor and improve my health or fitness.	
		I would voluntarily use wearable technology that provides online information about my health around sports practice to help me know what to do next and how to do it.	

was applied to suppress loading scores siting below ± .40. However, it is important to note that EFA identified a complex pattern of perceived quality of previous usage experience (PQ) and perceived information accuracy (PIA). One plausible reason is that participants may presume the quality of previous usage experience through the accuracy of information given by wearable technology. Indeed, this has been found in other studies suggesting that health information accuracy can lead to positive user experiences and the adoption intention of wearable healthcare technology subsequently (see, for example, Cheung et al., 2019). Following the data summarisation approach, this problematic item was therefore reasonable to be retained in the six-factor structure solution which six factors analysed in EFA were also considered interpretable (Fabrigar et al., 1999). For reliability, Cronbach alpha was assessed for each of the multidimensional constructs. All Cronbach's alphas ranged from .56 to .88 indicating an acceptable level of reliability (PQ α = .88; PIS α = .87; PWCU α = .56) (Kline, 2011).

The questionnaire aimed to address participants' differing levels of experience, such as self-efficacy with wearable technology, and their understanding of the technology. It consisted of three main parts aiming to: (i) provide a definition of a health technology; (ii) identify whether certain examples represented wearable technology; and (iii) provide a scenario of reference for the participants' consideration when responding to questions about willingness. These measurement items can be found in this link [https://doi.org/10.6084/m9.figshare.14095877.v1] (Chamorro-Koc, 2021).

3.3. Sample considerations

The population of interest was a representative sample of adults who considered themselves as a sport enthusiast or athlete. Two inclusion sampling criteria for this present study were: (i) over 18 years of age; and (ii) previously using any kind of health applications, or the health technology devices (e.g., Fitbit). Research respondents were recruited via email. Potential research respondents were recruited from the Queensland University of Technology, as well as Griffith University and the University of Queensland, with the survey link being disseminated among sports enthusiasts by the administrators in each university respective sport organisation. The survey link was also disseminated among athletes at the Queensland Academy of Sports (QAS), Queensland Weightlifting Association (QWA) and Queensland Australian Football League (QAFL). Before taking part of this research, respondents were provided with the information sheet and the consent statement ensuring that their responses were anonymous and strictly confidential. Considering the limitations of this present study, the process of data collection began during the COVID-19 pandemic in which certain restrictions limited the opportunities to collect data. At the end of the survey period, a total of 48 responses were collected. A post-hoc power analysis was conducted using G*Power, the statistical power analysis software. For the analysis reported, the present study achieved a power of .20; thus, this could be considered underpowered. Therefore, it is important to note that while the interpretation of the findings requires caution, future research could investigate the effects of larger sample sizes (Faul et al., 2007).

3.4. Data analysis and data cleansing

The questionnaire was created using the online survey software Key Survey. After the data collection period ended, the responses were imported to the IBM SPSS Statistics version 27 for analysis. Recoding was necessary for the values of some variables that had been coded inconveniently for analysis. For example, binary responses of 'yes' and 'no' (which previously coded as '1' and '2') were then recoded as '0' and '1' respectively. By doing so, these binary responses were easier to interpret for statistical analyses, including the testing of correlations.

When data cleansing was performed, a missing value analysis (MVA) was conducted on the data in SPSS to detect the pattern of missing data. This MVA analysis indicated that there was one problematic respondent with >15% missing data (Dong and Peng, 2013). Removing Respondent number 8 from the dataset was considered appropriate. However, although one respondent was removed, there was still a large percentage (<30%) of unengaged responses with similar missing value patterns which belonged to Questions, 44, 45 and 46. By looking at the response percentages for aforementioned questions, it was found that 38.3% of respondents did not answer both Questions 44 and 45 asking about how well their device represented their sleep, and whether their training load was modified according to their sleep monitored. Similarly, when Question 46 asked respondents about their intentions to continued usage of wearable devices for sleep monitoring, more than half of the respondents (61.7%) did not respond to this question. As indicated by the MVA results, the problem was centred around the questionnaire design, rather than unengaged respondents. One plausible reason is that the questionnaire was designed without forced-choice questions, thereby

Table 2. Exploratory factor loadings.

	Items	Factors					
		PA	PQ	PS	PIS	PIA	PWCU
PA	I was involved in choosing the wearable technology.	-.623					
PQ 1	The quality of your experience with the wearable technology device was:		.739				
PQ 2	My experience was:		.446			-.458	
PS	I was provided adequate information about who would see the data collected from the wearable technology.			-.835			
PIS 1	For data security and privacy, I was:				.960		
PIS 2	When my data recorded from wearable technology that is not secured and could be accessed by people without permission, I was				.821		
PIA	I was provided accurate information about what would be measured by the wearable technology (such as movement, location and heart rate).					-.806	
PWCU 1	I would voluntarily use wearable technology that tracks my activity or physical status during sports practice BUT NOT outside of my sports organisation: to monitor and improve safety from injury.						.720
PWCU 2	I would voluntarily use wearable technology that tracks my activity or physical status during my sports practice AND in my daily life: to monitor and improve my health or fitness.						.683
PWCU 3	I would voluntarily use wearable technology that provides online information about my health around sports practice to help me know what to do next and how to do it.						.475

Extraction Method: Principal Axis Factoring.
Rotation Method: Oblimin with Kaiser Normalization.

resulting in high missing values for certain questions. It is important to note that although this online questionnaire contained 46 questions, not all questions will be discussed in this present research paper.

4. Results

Based on a comprehensive review of the literature and relevant theoretical frameworks, survey questions were developed, reflecting six identified key variables. These variables were: (i) perceived autonomy; (ii) perceived quality of previous usage experience; (iii) perceived safety; (iv) perceived information security; (v) perceived information accuracy; and (vi) perceived willingness for continued use. The "perceived willingness for continued use" construct was considered a dependent variable in this analysis.

Data analysis followed a four-step procedure. First, characteristic of respondents, definitions of wearable technology given by respondents and their usage patterns were defined. Second, descriptive analysis provided the overview of responses for key variables that were used for assessing respondents' perceptions and trust in devices designed to self-monitor their health and performance. Third, a Mann-Whitney U Test evaluated the difference between the means of men and women in the dataset. This test was strongly underpinned by the Tests of Normality results. Fourth, the Pearson's correlation coefficient measured the strength, as well as the direction of the relationship between key variables.

4.1. Characteristics of participants

Demographic data of participants were collected, which allowed for the development of a profile of survey respondents with a special interest in wearable sports technology (see Table 3). Of the 47 useable responses from respondents who considered themselves "sport enthusiasts or athlete", females (70.2%) represented a larger proportion than males (29.8%). Most respondents were younger than 25 years (44.7%). Almost half of the participants (42.6%) practiced sports three times a week and had been participating seriously in sports for more than 10 years (44.7%). Of those, 87.6% participated in one to two sports. Considering sports participation settings, most participants revealed that they practiced their sport as individuals (87.2%). Sports practice was mainly for competitions (68.1%), rather than for health interest (31.9%). Results also indicated that most participants had their own coach when participating in sports (93.6%).

Table 3. Characteristics of participants.

Question		N	Valid %
Gender	Male	14	29.8
	Female	33	70.2
Age	Less than 25 years	21	44.7
	25–34 years	9	19.1
	35–44 years	10	21.3
	45–54 years	2	4.3
	55–64 years	2	4.3
	Greater than 64 years	3	6.4
Levels of sport participation	Several times everyday	10	21.3
	Daily	3	6.4
	Twice a week	3	6.4
	Three times a week	20	42.6
	Five days a week	11	23.4
How long you have been participating in sports seriously?	Less than 1 year	1	2.1
	1–5 years	17	36.2
	6–10 years	8	17.0
	More than 10 years	21	44.7
Sport participation settings	Team member	6	12.8
	Individual	41	87.2
Purpose of practising sports	Competitions	32	68.1
	Your own health interest	15	31.9
Number of sports	One	22	46.8
	Two	19	40.4
	Three	4	8.5
	Four	2	4.3
Do you have a coach?	No	3	6.4
	Yes	44	93.6

4.2. Usage patterns of wearable technology

To understand the usage patterns of wearable technology among participants, five statements were developed which allowed participants to select a statement that best described their wearable technology usage pattern (see Table 4). Among six different intended uses, results showed that over half of the participants had adopted wearable technologies to promote their health through fitness and activity monitoring (53.2%), while another quarter (25.5%) were monitoring their activity levels. Only a small proportion (2.1%) used their wearable technologies to receive instructions on how to perform their sports workout. Around 10% of participants stated other intended uses for the technology, such as to remind them about, and/or to monitor data regarding, 'food consumption', 'heart rate', 'calories', 'sleep' and 'training-session intensity'. When using wearable technologies, most participants (93.6%) reported that their use was voluntary. Most participants (97.9%) also said that they did not receive any incentive or bonus to use wearable technology (see Table 5). While wearable sensor technology was commonly used for monitoring training load and health, respondents (61.7%) were less interested in using their wearable technology devices for tracking their sleep patterns (see Table 6).

As can be seen in Table 7, most respondents (83%) intended to continue to use their wearable technology device in the future. However, more than half of them admitted that their future training would not be determined by metrics collected by their wearable technology device (53.2%). Similarly, more than half (57.4%) of the respondents indicated that they would not modify their training workload based on the metrics provided by their wearable technology.

4.3. Overview responses of key variables

Based on the descriptive statistics presented in Table 8, respondents seemed to gain some sense of autonomy, or perceived autonomy (PA), because they were substantially involved in choosing the wearable technology that they used (mean 4.26). For perceived quality of previous usage experience (PQ), overall results showed that respondents tended to have good experiences when using wearable technology devices (mean 4.06). Respondents seemed to be aware that wearable technology devices captured information by monitoring their activities. However, the overall responses of perceived safety (PS) were neutral (mean 3.30), indicating that respondents neither disagreed nor agreed that they were provided adequate information about 'who would see the data collected' from the wearable technology.

For perceived information security (PIS), the results showed that respondents felt little concern about how their information and data were kept secure and private from people without access permission (mean 2.00). With regards to perceived information accuracy (PIA), respondents agreed that they were provided adequate information about what metrics would be measured by their wearable technology device (mean 4.13). Nevertheless, their perceived willingness for continued use (PWCU) particularly in relation to the wearable technology was low across all three different usage situations (mean 2.12). This means that respondents seemed unwilling to voluntarily use wearable technology during sport practice or in their daily lives or both, even if wearable technology provided information concerning respondents' health and their sports practice.

Table 4. Intended uses of wearable technologies.

	N	Valid %
Monitoring productivity	12	25.5
Providing instructions about how to perform my work	1	2.1
Safety through monitoring my movement, activity, or physical state	2	4.3
Health promotion through fitness and activity monitoring	25	53.2
Unknown to me	2	4.3
Other (please identify)	5	10.6

Table 5. Motivations driving usage patterns of wearable technology.

	N	Valid %
Mandatory	3	6.4
Voluntary	44	93.6
Did not receive any incentive and/or bonus	46	97.9
Received any incentive and/or bonus	1	2.1

Table 6. Intended uses for tracking sleeping patterns.

	N	Valid %
For tracking sleeping patterns	18	38.3
Not for tracking sleeping patterns	29	61.7

4.4. Mann-Whitney test

Earlier research has noted gender differences which might exist among variables predicting acceptance of wearable technology (see, for example, Gore et al., 2016). While the independent samples t-test has been commonly used to compare differences between two independent groups, the Mann-Whitney U test is considered as the non-parametric alternative to the independent samples t-test particularly when data is not normally distributed (Batra, 2008; Zimmerman, 1987). As showed in Table 9, the present study ran a Shapiro-Wilk test which indicated for the rejection of null hypotheses of normal population distributions with the only exception being the PWCU at $p = .05$. As such, it can be concluded most variables in this study were not normally distributed (Shapiro and Francia, 1972; Yap and Sim, 2011).

Since non-normal data was detected in this study, the Mann-Whitney U test was used to compare differences between the six key variables based on gender. This study met the following four assumptions ensuring that this Mann-Whitney U test was most appropriate. First, the dependent variables in the present study were measured on the ordinal level. Second, the independent variable consisted of two categorical groups, male and female. Third, there was no relationship between observations between the groups themselves and in each group. Fourth and last, a Mann-Whitney U test was suitable when data was not normally distributed after conducting the Tests of Normality (Shapiro and Francia, 1972; Yap and Sim, 2011).

Table 10 provides information regarding the mean rank and the sum of ranks for the two groups tested: males and females. Overall, the male group had the higher mean ranks than the female group on the following four variables: PQ, PS, PIA and PWCU. Table 11 shows that perceived safety (PS) in the male group was statistically significantly higher than the female group ($U = 123$, $p = .010$). No statistically significant differences were found between the genders in the other five variables. Overall, the Mann-Whitney U test results indicate that males, compared with females, believed they were provided adequate information about who would see their data collected from wearable technology. Male respondents seemed to feel safe, even though they knew that their data might be collected by third parties.

Table 7. Intention for continuous use for training and modifying training workload.

	N	Valid %
Intend to continue use	39	83.0
Not intending to continue use	8	17.0
Training based on the metrics	22	46.8
Not training based on the metrics	25	53.2
Modify based on the metrics	20	42.6
Not modify based on the metrics	27	57.4

4.5. Pearson's correlation analysis

The present study conducted a Pearson's correlation analysis of the six key variables to understand the level of correlation among these variables. As presented in Table 12, the strongest correlation was found between perceived safety (PS) and perceived information security (PIS): $r = -.409$, $p = .004$. indicating that these variables move in opposite directions with relation to each other. This suggests that the more users feel they are provided information about 'who' would see their data collected, the less they feel concerned about information security and privacy, or, at least, they understand that their data could be assessed by second and third parties without permission.

Perceived safety (PS) had also a weak, negative correlation with perceived willingness for continuous use (PWCU): $r = -.289$, $p = 0.049$. This could indicate that when users are provided information about second and/or third parties accessing their data, users become more aware of their privacy and less willing to use their device again. Perceived information security (PIS) and perceived willingness for continuous use (PWCU) had a positive correlation: $r = .394$, $p = 0.006$. This indicates that despite concerns that using a wearable tech device is not entirely secure (because their data could be assessed by people without permission) they still intended to wear their device. This could be due, in part, to the influence of significant others, such as friends, coaches, personal trainers, or medical experts who are recommending the use of the device. This is something that future qualitative studies could explore in order to identify possible interventions or mediating variables.

Among the respondents who declared themselves as sport enthusiasts or athletes, perceived autonomy (PA) and perceived quality of previous usage experience (PQ) showed very weak positive correlation: $r = .302$, $p = 0.039$. This indicates that wearable tech users who have more autonomy tend to have had better experiences and are more satisfied with their wearable tech device. This has implications for User Interface (UI) and User Experience (UX) designers when it comes to designing the features of wearable tech devices, as the more autonomy users had when using a device, the more satisfied they were with the experience.

Interestingly, perceived autonomy (PA) and perceived willingness for continuous use (PWCU) had a weak, negative correlation: $r = -.309$, $p = 0.035$ indicating that whenever users have more autonomy, they are less enthusiastic for continuous use.

Perceived quality of previous usage experience (PQ) had weak positive correlations with perceived information accuracy (PIA) and perceived safety (PS): $r = .341$, $p = 0.019$ and $r = .376$, $p = 0.009$ respectively. These results indicate that when users understand what data will be measured when wearing their wearable technology device, and when they know 'who' will see the data collected, they tend to feel positive or satisfied with their device.

5. Discussions and conclusions

5.1. Key findings

Findings reveal that the respondents, as sport enthusiasts or athletes, wear their health technology voluntarily and with an intention to track one or two aspects of their body data; however, for the majority, the use of the technology and data output does not drive their health goals or

Table 8. Overview responses of key variables.

Items	Mean	SD
Perceived Autonomy (PA)	4.26	
I was involved in choosing the wearable technology	4.26	1.224
Perceived Quality of Previous Usage Experience (PQ)	4.06	
The quality of your experience with the wearable technology device was:	4.17	0.892
My experience was:	3.96	0.884
Perceived Safety (PS)	3.30	
I was provided adequate information about who would see the data collected from the wearable technology	3.30	1.214
Perceived Information Security (PIS)	2.00	
For data security and privacy, I was:	2.00	1.043
When my data recorded from wearable technology that is not secured and could be accessed by people without permission, I was:	1.98	.944
Perceived Information Accuracy (PIA)	4.13	
I was provided accurate information about what would be measured by the wearable technology (such as movement, location and heart rate)	4.13	.769
Perceived Willingness for Continuous Use (PWCU)	2.12	
I would voluntarily use wearable technology that tracks my activity or physical status during sports practice BUT NOT outside of my sports organisation: to monitor and improve safety from injury	2.40	1.330
I would voluntarily use wearable technology that tracks my activity or physical status during my sports practice AND in my daily life: to monitor and improve my health or fitness	1.98	1.277
I would voluntarily use wearable technology that provides online information about my health around sports practice to help me know what to do next and how to do it	1.98	1.032

Note:
PA = Perceived Autonomy (five-point Likert: ‘Not Involved = 1’ and ‘Extremely Involved = 5’).
PQ = Perceived Quality of Previous Usage Experience (five-point Likert: ‘Very Bad = 1’ and ‘Very Good = 5’).
PS = Perceived Safety (five-point Likert: ‘Strongly Disagree = 1’ and ‘Strongly Agree = 5’).
PIS = Perceived Information Security (four-point Likert: ‘Not Concerned = 1’ and ‘Very Concerned = 4’).
PIA = Perceived Information Accuracy (five-point Likert: ‘Strongly Disagree = 1’ and ‘Strongly Agree = 5’).
PWCU = Perceived Willingness for Continuous Use (five-point Likert: ‘Strongly Disagree = 1’ and ‘Strongly Agree = 5’).

intentions regarding their sports practice. Findings address the research question and indicate some of the factors that play a role in enabling self-efficacy and trust in consumers' use of health-technologies devices for sports are:

- **Their past experiences of using health tech in the context of use (sports) play a role in people's perception of self-efficacy.** Our survey helped identify some of the key factors that determine participants' sense of self-efficacy when using health technology devices for their sports activities. The participants' responses identified three factors: (i) *use-case scenarios* indicating participants' use of health technology for sports, (ii) their *past experiences* with health technology for sports as a determining factor for their engagement with the technology, and (iii) *their individual opinion* about the use of health technology in sports. As illustrated in Figure 1, all three factors seemed to contribute as foundation to determine a personal sense of self-efficacy and a positive experience in using health technology for sports. The analysis and results regarding perceived autonomy (PA) provided indications about the participants' confidence, satisfaction, trust, and privacy issues. Associated positive experiences in the use of a health technology for sports practice are related to autonomy in choosing what technology to use and when to use it. In addition, results also suggest that these factors are relevant to the respondent's tendency to make the most use of their device for tracking and monitoring performance, rather than using metrics to improve their health. These insights expand on current studies showing that perceived motivational properties and technology usability are indicative of user's trust and their intention to adopt wearable technology devices (Marangunic and Granic, 2015; Rupp et al., 2016; Beldad and Hegner, 2017). It also expands on theories about past

Table 9. Tests of normality.

Variables	Shapiro-Wilk			
	Gender	Statistic	df	Sig.
Perceived Autonomy (PA)	Men	.776	14	.003
	Women	.573	33	<.001
Perceived Quality of Previous Usage Experience (PQ)	Men	.850	14	.022
	Women	.898	33	.005
Perceived Safety (PS)	Men	.861	14	.032
	Women	.913	33	.011
Perceived Information Security (PIS)	Men	.850	14	.022
	Women	.889	33	.003
Perceived Information Accuracy (PIA)	Men	.767	14	.002
	Women	.811	33	<.001
Perceived Willingness for Continuous Use (PWCU)	Men	.921	14	.225
	Women	.914	33	.013

Table 10. Ranks of the Mann-Whitney U test.

	Gender	N	Mean Rank	Sum of Ranks
PA	Male	14	19.29	270.00
	Female	33	26.00	858.00
	Total	47		
PQ	Male	14	25.82	361.50
	Female	33	23.23	766.50
	Total	47		
PS	Male	14	31.68	443.50
	Female	33	20.74	684.50
	Total	47		
PIS	Male	14	23.57	330.00
	Female	33	24.18	798.00
	Total	47		
PIA	Male	14	26.79	375.00
	Female	33	22.82	753.00
	Total	47		
PWCU	Male	14	25.86	362.00
	Female	33	23.21	766.00
	Total	47		

Table 11. Test statistics of the Mann-Whitney U test.

	PA	PQ	PS	PIS	PIA	PWCU
Mann-Whitney U	165.000	205.500	123.500	225.000	192.000	205.000
Wilcoxon W	270.000	766.500	684.500	330.000	753.000	766.000
Z	-1.860	-0.609	-2.576	-0.143	-0.970	-0.613
Asymp. Sig. (2-tailed)	0.063	0.542	0.010**	0.886	0.332	0.540

**. Correlation is significant at the 0.01 level (2-tailed).

Table 12. Pearson's correlations among key variables.

Key variables	PA	PQ	PS	PIS	PIA	PWCU
Perceived Autonomy (PA)	-					
Perceived Quality of Previous Usage Experience (PQ)	.302*	-				
Perceived Safety (PS)	.123	.376**	-			
Perceived Information Security (PIS)	.050	-.179	-.409**	-		
Perceived Information Accuracy (PIA)	.195	.341*	.168	.062	-	
Perceived Willingness for Continuous Use (PWCU)	-.309*	-.400**	-.289*	.394**	.030	-

*. Correlation is significant at the 0.05 level (2-tailed).
**. Correlation is significant at the 0.01 level (2-tailed).

experiences as predictors of anticipated positive experiences (Yogasara et al., 2011) identified for personal interactive technology products, but not for personal sports or health related devices.

- **The tracking of activities enables autonomy and confidence**. In this study, results about perceived autonomy (PA) provided indications about our participant group of sport enthusiasts or athletes *confidence in their use of wearable technologies* to promote their health through tracking their activity (Table 8) and indicated that such technologies enable their *autonomy*. This is an additional factor to *satisfaction* from previously using a wearable technology, as well as an overall *positive experience* of using wearable/health technologies for sports. These findings align with much of the current literature indicating that individuals engage more with health technology devices if they are involved in activities that meet the core psychological needs of autonomy, relatedness, and competence (Sundar et al., 2012; Chang et al., 2016; Kerner and Goodyear, 2017; Molina and Sundar, 2020). As illustrated in Figure 2, facilitating a user's autonomy, in the form of user customisation and choice, and competence, in the form of easy-to-use and reliable devices, as described by the Technology Acceptance Model (Beldad and Hegner, 2018; Davis, 1989; Marangunić and Granić, 2015) have been well established as motivators in the use of health technology (Chang et al., 2016; Kerner and Goodyear, 2017; Molina and Sundar, 2020; Sundar et al., 2012). This research found a weak positive correlation between *perceived autonomy* and the *perceived quality of a previous use* (Table 12), lending support to the findings of the aforementioned research, and further highlighting the implications autonomy has for user interface (UI) and user experience (UX) design.
- **Autonomy influences personal willingness to use health technologies**. Interestingly, the factors of *perceived autonomy,* and *perceived* quality *of a previous use,* had a weak negative correlation with a user's *perceived willingness for continued use* (see Table 12), suggesting that when a user has more autonomy and feels positive about their activity experience, they are less likely to be willing to use

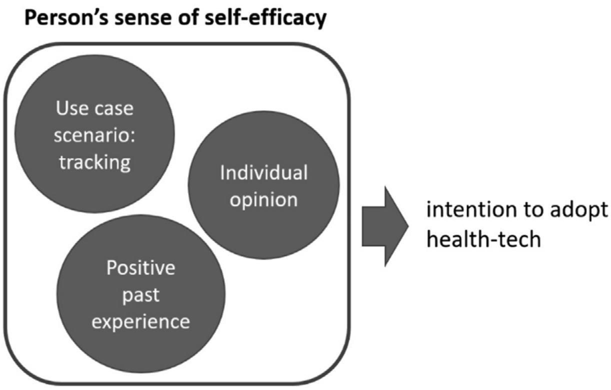

Figure 1. Self efficacy and intention to adopt health-technology.

a device. This means that engagement with health technology devices may also depend on the persona profile of individuals (Nicholas et al., 2015) and personal factors such as motivation, achievement, and self-regulation (Bandura, 2006). This may seem paradoxical, but could potentially be explained by a confounding variable, such as being persuaded to use a device they would not have chosen for themselves by a coach or medical practitioner. Further qualitative research is recommended to identify key attributes that are salient to different types of health technology users (user profiles) and how those factors of use (perceived autonomy and perceived quality of previous use) perform for different users (see Figure 3).

- **Strong interest in personal health motivates engagement with health technology**. As illustrated in Figure 4, physically active people have a stronger awareness and interest in their personal health, leading them to engage more with such technology (Rupp

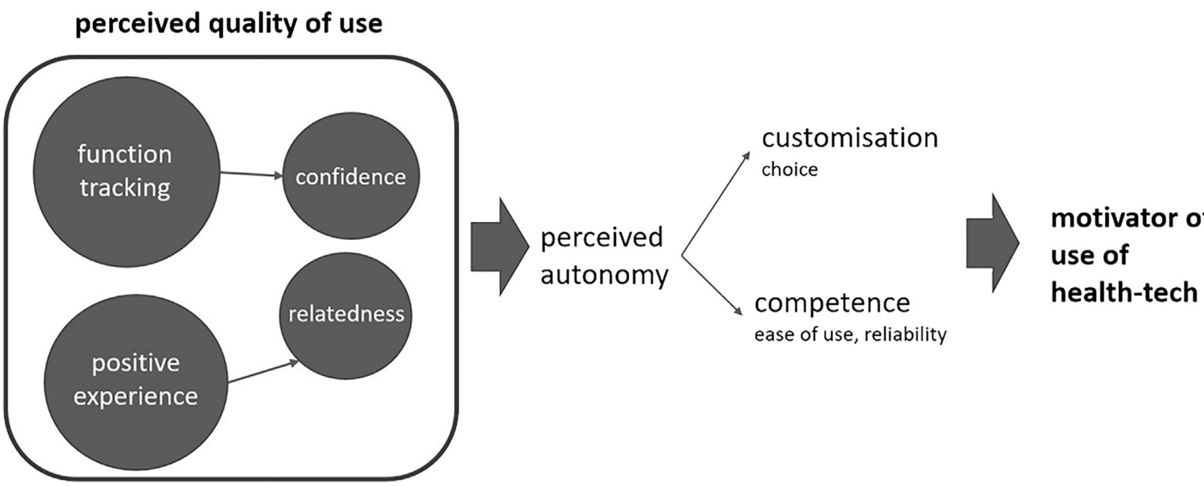

Figure 2. Perceived quality of use and motivation to use health-technology.

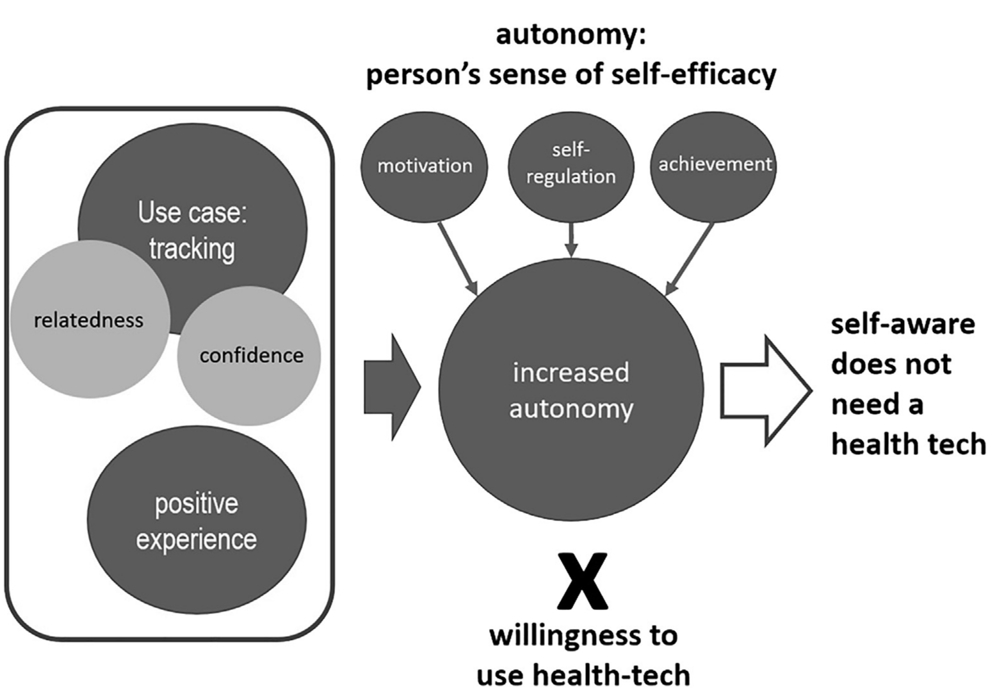

Figure 3. Autonomy and willingness to use.

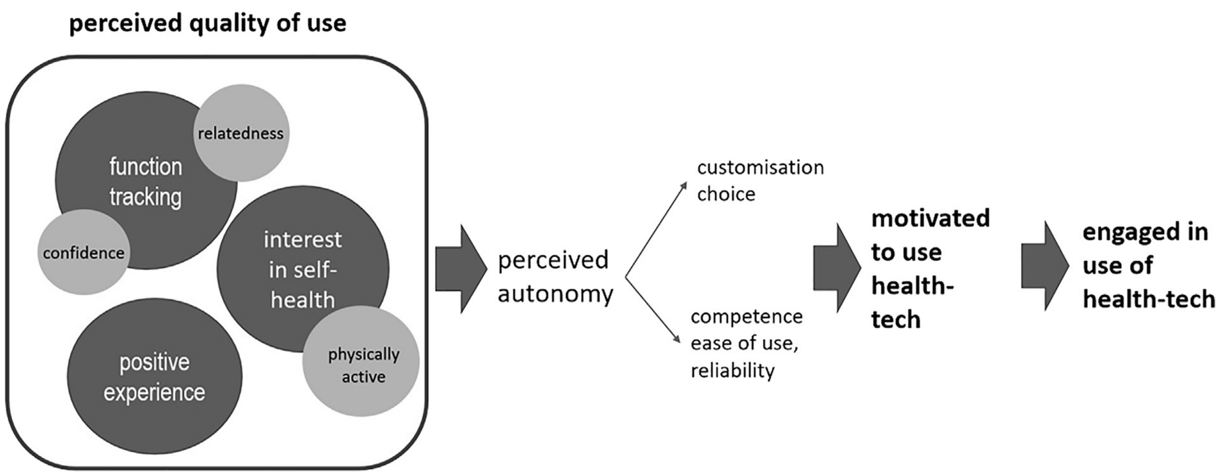

Figure 4. Perceived quality of use, Autonomy and Motivation to use.

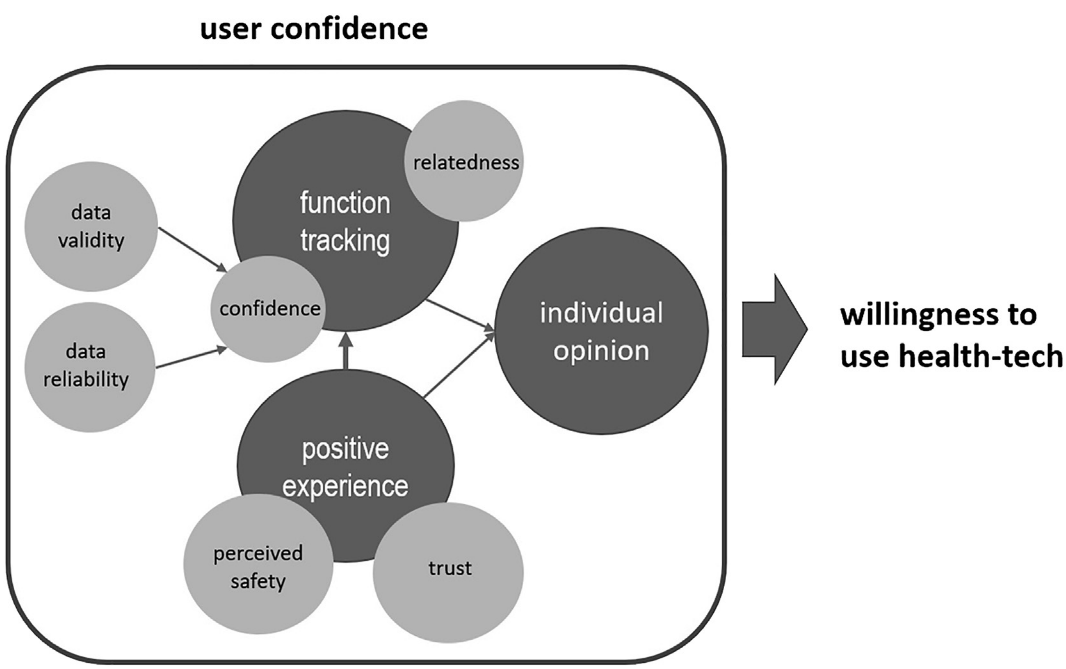

Figure 5. User confidence and Willingness to use.

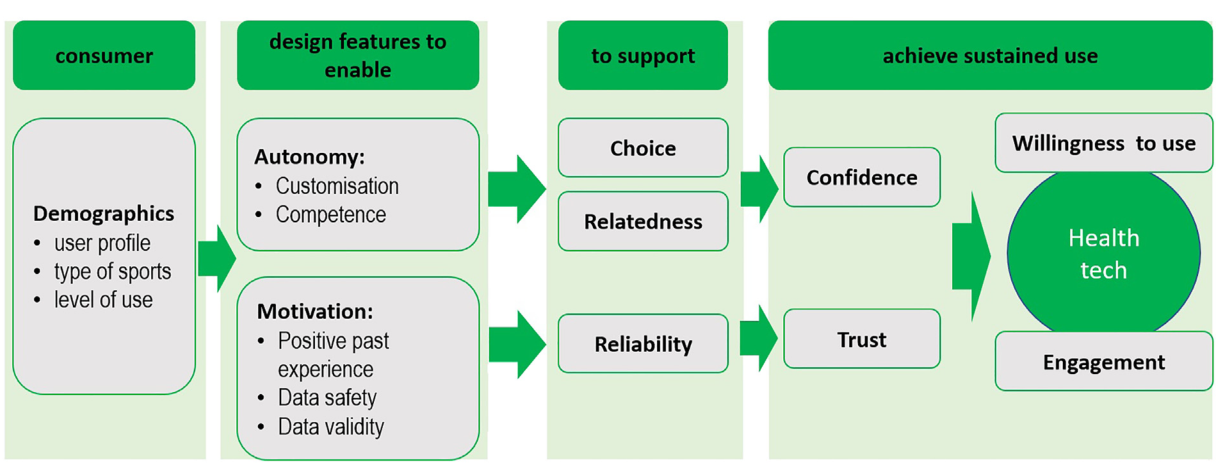

Figure 6. Conceptual model for the design of health technologies.

et al., 2018). We know from Rupp et al. (2018) that more active individuals, with more experience in engaging in exercise, find health technology features more motivational than those who are less active. In this research we expanded on this notion, and add that to predict a positive experience, *autonomy* should be included as one of the factors when assessing end users' satisfaction with the technology. Therefore, in our view, supporting self-efficacy mechanisms for sports enthusiasts requires the creation of positive user experiences by enabling people to have a sense of satisfaction and autonomy.

- **Reliability and validity of data impacts on confidence in health tech**. User confidence in a health technology is dependent on the validity and reliability of its data, as well as the usefulness of its features for attaining their fitness goals (Davis, 1989; Marangunic and Granic, 2015; Rupp et al., 2016; Beldad and Hegner, 2018). This study has also shown that for this group of sport enthusiasts, trust and data safety were not determinants of use of the technologies but did cause some level of concern about data security and safety (Figure 5). Among the variables that were tested, the strongest correlation was found between *perceived safety* and *perceived information security*. Perceptions of safety increased as concern about information security decreased (see Table 12), lending support to the findings of Chang et al. (2016) and Rupp et al. (2016) who described how information protection influenced a user's trust in a technology. Interestingly, perceived safety and concern about information security had weak, negative correlations with willingness to continue use, raising questions about these factors that could be addressed in future research. Our findings do not provide a strong indication that trust and data safety lead to negative experience in the use of wearable/health technologies in sports.

Peake et al. (2018) advised companies producing health technologies to engage in research with end users to identify the real world needs of the consumer. This research has contributed to this end by highlighting factors that influence sport enthusiasts or athletes' willingness to continue use of a health technology. The results regarding the factors enabling self-efficacy mechanisms supporting people's decision-making process about their health, and other factors identified in the current literature, were used to inform a conceptual model (Figure 6) illustrating the relationship amongst all identified factors enabling self-efficacy and trust in consumers' use of health-technologies devices for sports. We propose this conceptual model for developers to consider when designing or evaluating health technologies:

Our conceptual model that takes into consideration *demographic* differences (age, type of sports, previous experience with health technology) as key differentiators of the type of *motivation* (customisation and competence) *and autonomy features* (positive past experiences, perceived data safety and data validity) that the health technology design needs to convey to support consumers' choice, relatedness and reliability. Such features would support *trust* and *confidence* in the use of the technology. This system of features that consider design features supporting consumers' perceptions of choice, relatedness, and reliability according to their demographics, would in turn lead to consumers' willingness to use a health technology device. We infer that the overall result of these factors adds to a user's trust in a health technology, supports a user's self-efficacy and enables the user's decision-making process and engagement with their health goals.

Further research is required to develop this model, with the aim of informing designers and developers of how to translate these factors that trigger people's perceptions of value, trust and continued use of health technology devices, into design features for the development of more effective personal health technology.

5.2. Limitations

This survey was implemented between September and November 2020. This period was characterised by COVID-19 limitations in most cities globally. While this study was conducted in Brisbane (Australia) with minimal restrictions, the effects of COVID had influenced people's routines and sports practices, especially at public gyms and sporting facilities. The specific limitations in our study included the number of respondents, and demographic representation in the analysis. Our survey reached the expected number of respondents (>30, actual respondents = 48) but lacks the statistical power of a larger sample size. Our sample is only representative of the athletic population of Queensland, Australia and is, as such, biased by the cultural norms of the region. The sample did not cover all possible sports or athletic pursuits and it may also by biased by overrepresented modalities of exercise and sporting practice. Because the survey addressed perceptions of sport enthusiasts or athletes, the survey's analysis is not representative of those who are less involved in sports.

Declarations

Author contribution statement

Marianella Chamorro-Koc, Jonathan Peake, Adam Meek, Guljira Manimont: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

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Data availability statement

The authors do not have permission to share data.

Declaration of interests statement

The authors declare no conflict of interest.

Additional information

No additional information is available for this paper.

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