informatics

MDPI

Article

From Data to Behaviour: Understanding the Perceived Smartwatch Value for Physical Activity Through Self-Quantification

Carmen Bekker *, Brenda M. Scholtz and Simone Beets

Department of Computing Sciences, Nelson Mandela University, Port Elizabeth 6031, South Africa; brenda.scholtz@mandela.ac.za (B.M.S.); simone.beets@mandela.ac.za (S.B.)
* Correspondence: carmen.bekker@mandela.ac.za

Abstract

Smartwatches are commonly used IoT wearable devices, which contain sensors that can support the data management process of smartwatch data. This process is essential for providing data-based insights that can motivate users to achieve their physical activity (PA) and health goals. However, there is a lack of understanding of users' perceptions of the health-related value they derive from smartwatches and of user self-tracking behaviour within a PA context. This self-tracking behaviour is also known as Self-Quantification Behaviour (SQB), which is the process of data preparation, collection, integration, reflection, and action. SQB could be affected by the functions provided by the smartwatch device, which vary by manufacturer, brand and model. The paper aims to investigate user perceptions of SQB and its association with their perceived value of smartwatches. A survey was conducted with professional office workers from South Africa who use smartwatches. The findings highlighted that the respondents enjoyed collecting and engaging with their PA data and that SQB significantly affected all four value constructs: Perceived Usefulness, Pleasure, Goal Pursuit Motivation, and Social Value. Social value, in terms of data sharing and user lifestyle, was the least well-rated. The findings contribute to an enhanced understanding of smartwatches and users' perceived value of self-quantifying behaviour in the context of PA, thereby ultimately improving the smartwatch usage experience and motivating users to exercise more.

Keywords: Internet of Things (IoT); smartwatch sensors; self-quantification behaviour (SQB); physical activity (PA); smartwatch value

Check for updates

Academic Editor: Roberto Theron

Received: 29 April 2026
Revised: 21 June 2026
Accepted: 2 July 2026
Published: 9 July 2026

Copyright: © 2026 by the authors. Licensee MDPI, Basel, Switzerland. This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license.

1. Introduction

Technological advancements in sensors impact the digital value chain and provide benefits and value to stakeholders, such as smartwatch users, manufacturers and medical practitioners [1,2]. Sensors related to the Internet of Things (IoT), for example, in mobile health (m-health) and in smart homes, generate data that provide value and new opportunities across fields such as healthcare and biomedical informatics, and improve quality of life [1,3–5]. Smart devices, such as smartwatches, enable the collection of data-based insights into physical activity (PA), sleep patterns, and health-related behaviours [6–9]. Smartwatches are commonly used wearable IoT, which are smart computing devices that contain sensors that assist in the detection, tracking, and analysis of physiological and biological data related to health and fitness [10–12]. The study of Ha et al. [13] confirmed

that users are interested in the health and fitness functionality provided by smartwatches. Similarly, Stiglbauer et al. [14] highlighted that smartwatch users could experience significant improvements in their physical health, feelings of accomplishment, and emotions when smartwatches are used in combination with their companion mobile applications (apps). Smartwatches and their companion apps can be used to promote PA by providing personalised feedback that addresses the users' PA behaviour [15,16].

Smart device features and functions, such as visualising goal achievement, can increase the ease of data interpretation for smartwatch users and enable Self-Quantification Behaviour (SQB), which is commonly referred to as self-quantification [10,17,18]. SQB refers to the processes of data preparation, data collection, data integration, personal reflection, and action that users engage in, relevant to their PA, when using a smartwatch and its companion app.

In the study of Kang and Jung [19], it was reported that larger volumes of collected and analysed smartwatch data lead users to perceive greater value in their smartwatch, which refers to the extent to which users believe they will benefit from using the device [7]. Since the data are collected during the SQB process, it follows that SQB impacts value.

The perceived value of smartwatches for PA can be classified into utilitarian, hedonic, and social value. Utilitarian value in the context of smartwatches refers to the benefits derived from using the device to complete tasks [20]. This type of value focuses on smartwatch utility, performance, and functions [21]. For example, since smartwatches are equipped with various sensors, users can monitor and improve their health and fitness. These functions vary depending on the manufacturer, brand and model of the device. The hedonic value of smartwatches refers to the pleasurable, emotional or entertainment rewards from using them, including achieving one's goal of a certain step count per day [22] or earning trophies through gamification [21]. However, studies examining the impact of smartwatch SQB on value yield conflicting results. For example, Zhang et al. [23] proposed that SQB positively affects hedonic value through perceived enjoyment when users have set PA goals. Conversely, Huh et al. [22] and Etkin [24] argued that SQB has a positive effect on PA performance but a negative one on hedonic value, specifically enjoyment. According to Kamal Basha et al. [21], smartwatch social value is the benefit gained from using a smartwatch through the maintenance and improvement of social relationships. For example, smartwatch users can share their data, connect with friends and family, or meet others through communities in smartwatch apps.

The study by Cho et al. [10] highlighted a research gap in analysing the constructs that affect users' perceptions of smartwatch value. Understanding the value of smartwatches could guide their design to motivate and encourage users to improve their PA and reduce health-related issues stemming from high levels of sedentary behaviour. In companies, reducing sedentary behaviour by encouraging PA can improve employee health and productivity and reduce absenteeism due to poor health [25–28]. The study by Meyer et al. [29] focused on healthy physical work habits among software developers through reflective goal setting. However, the focus was not specifically on the PA of smartwatch users, and the study participants resided primarily in developed economies, including the United States, Canada, and Switzerland. Brazil was the only developing economy in the study included in the population. Therefore, more research on smartwatches is required from a developing-economy perspective, such as that of South Africa, where office workers tend to be sedentary for approximately 9.9 h per day [30]. There is a need to understand how data collected from users and managed by smartwatches can transform human behaviour in ways that positively affect their health. The purpose of this paper is to investigate the associations between SQB and the perceived value of smartwatches across utilitarian, hedonic, and social value.

The subsidiary research questions are as follows:

RQ1: What are users' perceptions of smartwatch SQB?

RQ2: How does SQB affect the perceived value of smartwatches?

The scope and context of the paper are smartwatches used by office professionals, whose work is mostly desk-bound, therefore contributing to sedentary behaviour. The paper's contribution is: (1) A model that illustrates the relationships between the smartwatch device brand and SQB, and between SQB and the value constructs, and (2) insights into user perceptions of the functions and activities of smartwatches related to the SQB process.

The paper is structured as follows: Section 2 provides the literature review. Section 3 presents the hypotheses to be tested and the developed research model. Section 4 explains the positivistic approach followed and the related materials and methods. Section 5 provides the results of the statistical analyses. Section 6 presents a discussion of the results and key findings. Section 7 concludes the paper.

2. Literature Review

2.1. Physical Activity (PA), Smartwatch Self-Quantification Behaviour (SQB), and Brand

PA is body movement that expends energy generated by skeletal muscles and provides health and well-being benefits [31]. Regular PA engagement, such as walking or cycling, reduces the risk of numerous diseases, including cardiovascular disease and diabetes; assists with weight management; and promotes mental well-being [26]. PA can also increase networking and socialisation opportunities, thereby positively impacting communities and society by promoting social interaction and cohesion. From a community and economic perspective, increased PA among individuals improves workplace productivity and reduces absenteeism and employee turnover.

To achieve improvements in health and physical well-being, changes in movement patterns need to be detected to guide individuals with their workouts and with adjusting their lifestyles, and the data needs to be accurate [8]. Therefore, it is important to understand the data management process for smartwatch data. Data management refers to the development, execution, and monitoring of practices, policies, plans, and programs that protect, control, improve, and deliver the value of information [32]. It follows, therefore, that the data management of smartwatch data influences the value of smartwatch information. Another concept related to data management is SQB, which has been described as a form of personal informatics, in which self-quantified users collect their PA data to support self-reflection [33]. The five-stage model of personal informatics systems proposed by Li et al. [34] and successfully adopted by Maltseva and Lutz [17] was extended in this paper and is presented in Figure 1.

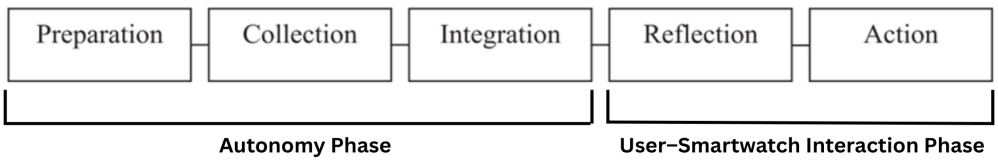


Figure 1. The SQB process for smartwatches—extended from Li et al. [34].

The first three stages of the SQB process for smartwatches can be considered the phase in which autonomy occurs since, according to Cho et al. [10], autonomy involves real-time, autonomous data collection; self-managed activities; and sensors and functions that do not require user intervention. In the first stage, namely the preparation stage, the smartwatch user's motivations for collecting their PA data are described. These motivations can be, amongst others, goal achievement, feeling a sense of personal improvement, an interest in PA data, or curiosity about physical behaviours. The second stage, the collection phase, consists of data collection, during which the smartwatch sensors autonomously collect data

required to determine the intensity of PA or workouts [10,35]. The functionality of these sensors is continually improving, with manufacturers adding new features and sensors to newly released smartwatch models. Therefore, these sensors vary by brand and model, affecting the accuracy of the smartwatch data (including PA data) [15]. The studies by El-Amrawy et al. [15], Ricchio et al. [36], and Nelson et al. [37] highlighted the importance of users' access to accurate information for self-quantifying their behaviour, as error rates in step count and heart rate data collection can be high.

Step count and heart rate data are primarily required to calculate PA. The sensors used for autonomously collecting and analysing step count data include a gyroscope and a three-axis accelerometer [15,21,36]. Since smartwatches are wrist-worn, changes in movement, such as when running or walking, are detected by the sensors and measured by an individual's arm swing [36]. Heart rate data from smartwatch users is usually collected in beats per minute using light-emitting diodes (LEDs) [15,21,36]. The LEDs are used to estimate heart rate by reflecting light onto a user's skin to detect changes in blood volume within the capillaries [15,36]. Green LEDs consume less battery life and are more cost-effective than red LEDs. However, red LEDs are more precise than green LEDs. Using a combination of green and red LEDs, along with more LEDs, increases heart rate data accuracy.

During the integration stage, the collected data is processed, integrated, and transformed, and then used to calculate health metrics using algorithms specific to the smartwatch manufacturer or brand [21]. Data is often stored temporarily and locally in the smartwatch's random-access memory (RAM) after processing, then transmitted to a companion mobile app that provides greater storage capacity [38,39]. The stored data can then be accessed from the companion app in a variety of formats, such as comma-separated values (CSV), JavaScript Object Notation (JSON), or eXtensible Markup Language (XML), via the export function or other means [38,40]. The smartwatch data can then be analysed, with the type of analysis dependent on the research approach, the user's goal, and the file format of the exported data.

The second phase of the SQB process for smartwatches is user–smartwatch interaction (also referred to as smartwatch interaction), which refers to the activities and communication between a user and their smartwatch, such as using the watch's health-monitoring app(s) in real time [10,21,41,42]. Examples of smartwatch interaction functions include data sharing, goal setting and adaptation, and visualising insights. All these functions depend on the successful completion of the autonomy phase. Goal setting and adaptation allow users to set and adjust their PA goals [42]. In this way, the watch serves as a motivational tool that helps them achieve their personal goals, for example, increasing PA.

The smartwatch interaction phase incorporates the reflection and action stages, as it is where smartwatch users interpret their data, reflect on the provided insights, and then take action to adjust or maintain certain behaviours [17]. Sophisticated, visualised insights can be presented on the smartwatch or companion app, allowing users to receive instant feedback and adjust their behaviour accordingly. Commonly used visualisations include bar, doughnut, and radial bar charts to present data such as heart rate and step count [43]. Once the PA and other health data have been collected by smartwatch sensors, social interaction and sharing functions can be provided to users. Sharing functions allow users to share their smartwatch data insights with friends, family, and peers to receive emotional support regarding their progress, for example, of their PA [44].

A similar process for SQB to that shown in Figure 1 was identified by Almalki et al. [45] in the context of a personal health information self-quantification system using wearable sensors, consisting of six phases: understanding the role; managing data; reflecting on the data; building knowledge; taking action; and managing behaviours. This process

enables wearable users to learn about their PA behaviours and derive value from their smartwatches as they work toward informed, data-driven health outcomes. However, the process proposed by Li et al. [34], extended in the present research (as shown in Figure 1), was used in this paper to explain the concept of SQB.

2.2. Smartwatch Value, Satisfaction, and Continued Usage

Several studies [10,18,21,41] have investigated smartwatch user satisfaction and value and how different factors affect both constructs. Satisfaction refers to a user's reaction or feelings after comparing their expectations of a smartwatch with their experience in using the device [10,18,41]. On the other hand, value or perceived value is a user's subjective perception of worth when using a smartwatch, based on considerations of costs, benefits, and trade-offs [21]. Satisfaction and value can be considered closely related, though not identical, concepts, as the measurement items overlap conceptually (e.g., enjoyment, pleasure, and usefulness) [21]. This relationship was confirmed by Luo et al. [46], specifically for health-related value. Users are more satisfied with their smartwatches when they provide greater utilitarian health-related value [46].

The effect of constructs such as satisfaction and value on a user's intention to continue using a smartwatch, also known as Continuous Usage Intention (CUI), has been explored in several studies [10,18,21,41]. CUI refers to a situation in which individuals identify a continued use of an action [47]. The studies of Cho et al. [10], Siepmann and Kowalczuk [18], and Bölen [41] determined that satisfaction has a positive impact on CUI. The study by Kamal Basha et al. [21], on the other hand, found that perceived value positively impacts CUI. This perceived value encompasses utilitarian, hedonic, social, and symbolic value. The study by Lin and Windasari [48] highlighted that a user's daily routine (i.e., CUI) and their interaction with a smartwatch contribute to value creation, suggesting that potential smartwatch value can be measured by observing users' pre-existing CUI.

The influence of SQB on CUI and value is rarely explicitly stated in the studies by Cho et al. [10], Siepmann and Kowalczuk [18], Kamal Basha et al. [21], and Bölen [41]. Whilst the study of Siepmann and Kowalczuk [18] identified that SQB has an indirect impact on CUI value through the constructs of Goal Pursuit Motivation (GPM) and Perceived Usefulness (PU), it focused mostly on emotional factors and did not investigate the association between SQB and these constructs within all three dimensions of utilitarian, hedonic, and social value.

2.3. SQB and Utilitarian Value: Perceived Usefulness (PU)

Despite several studies [10,18,21,41] using different theories to determine how various constructs impact CUI and, therefore, value, there was often overlap in the identified constructs, such as PU and pleasure. PU refers to the perceived benefits users derive from using a technology, such as a smartwatch, and includes a user's expectations of that technology [41]. From a smartwatch perspective, PU is the likelihood that wearable self-tracking devices will support self-tracking or self-quantified users in health tracking, habitual data capture, and achieving their goals related to PA and weight loss [49]. PU can be considered a type of utilitarian value, as it reflects the benefits users gain from completing tasks with a smartwatch, the smartwatch's utility, and its performance [41].

Few studies have examined the relationship between SQB and PU [18] and instead have focused on PU and CUI [21,41]. According to Pfeiffer et al. [49], prior studies on PU were mostly conducted using the Technology Acceptance Model, which found that PU was the strongest predictor of technology adoption, user acceptance, and user behaviour. A study by Siepmann and Kowalczuk [18] revealed that SQB affects PU as users become more familiar with their smartwatch's functionality over time. However, the study focused only

on German smartwatch users who often use self-tracking devices or have used them in the past, which, according to Findeis et al. [50], indicated high levels of SQB in their sample.

2.4. SQB and Hedonic Value: Pleasure and Goal Pursuit Motivation (GPM)

In the context of smartwatches, users can derive pleasure from their collected PA data or other SQB activities, such as participating in competitions with family and friends [10,18]. Pleasure refers to the positive feelings that users experience, which are derived from the emotional and hedonic benefits that smartwatch functions provide [10,51,52]. The prior studies of Cho et al. [10] and Siepmann and Kowalczuk [18] used the terms "pleasure" or "enjoyment" to assess the impact of these constructs on satisfaction and, by extension, value in their proposed models. The concept of pleasure is similar to that of enjoyment, since enjoyment refers to the pleasure users experience when using a smartwatch [18].

The study by Huh et al. [22] found that SQB positively influences the performance of a behaviour, such as PA, but may reduce the pleasure derived from performing an activity and therefore negatively affect hedonic value. In these cases, users feel as though PA is work or a chore rather than enjoyable, since achieving a specific outcome is their main priority [23].

From a positive relationship perspective between SQB and pleasure, Oppermann [53] found that gamification features, such as challenges, leaderboards, and trophies, in combination with PA feedback, trigger feelings of pleasure and happiness among smartwatch users. Other studies, such as those of Zhang et al. [23] and the World Health Organization (WHO) [28], also found that SQB positively affects users' hedonic value, specifically pleasure.

SQB enables smartwatch users to track and maintain progress toward their goals by collecting personal data during goal pursuit, such as during PA. According to Siepmann and Kowalczuk [18], SQB affects GPM by improving the perception that goals are attainable through feedback from smartwatches. According to Oppermann [53], loss of GPM is one of the main reasons that users stop self-tracking, along with the perceived costs of data collection and integration. Loss of motivation results from unmet expectations of success, which then leads to disengagement from self-tracking or SQB. However, SQB can be a source of both positive and negative feedback when pursuing long-term goals [22]. Even if daily results are not always apparent regarding a user's appearance, quantified measures, such as daily step count, can assist users in staying motivated to engage in PA regularly.

In a PA context, health-related constructs, such as GPM, and social constructs that affect the value that smartwatches provide to users were not commonly considered in the models of Cho et al. [10], Kamal Basha et al. [21], and Bölen [41]. GPM was one such health dimension proposed by Siepmann and Kowalczuk [18] and refers to the motivational levels of smartwatch users in working towards their set health and fitness goals. These authors [18] argued that GPM is a dimension of hedonic value, as smartwatches often include gamification features to help users stay motivated to pursue their goals.

2.5. SQB and Social Value

SQB has been shown to affect self-disclosure, which refers to any information or messages about an individual that are communicated to or shared with someone else [17]. Sharing personal data via a smartwatch or a self-tracking app develops into a regular habit for users in both social situations and on an individual level and therefore forms part of social value. Smartwatches enable social interaction through data-sharing functions, allowing users to compete with one another, exchange information about their PA, and receive motivational support from their community's recognition of their achievements [44,53]. If smartwatch users perceive that providing the smartwatch or companion app with more personal data (e.g., age, weight, and height) increases data accuracy, then self-disclosure and

data-sharing actions become behavioural habits over time [17]. Therefore, self-disclosure can be considered communication and data sharing, which are part of SQB and contribute to social value. The studies of Asimakopoulos et al. [6] and Pennington and Dam [54] reported that social interaction and data sharing among smartwatch users positively influence a user's PA engagement, user–smartwatch interaction (which forms part of SQB), and CUI. Since CUI directly influences perceived value, it can be deduced that SQB affects social value.

3. Hypotheses and Research Model

Several associations between SQB and the different constructs of smartwatch value were identified in the literature review and are modelled in Figure 2. Based on the literature, hypotheses were developed regarding the relationships between SQB and these constructs.

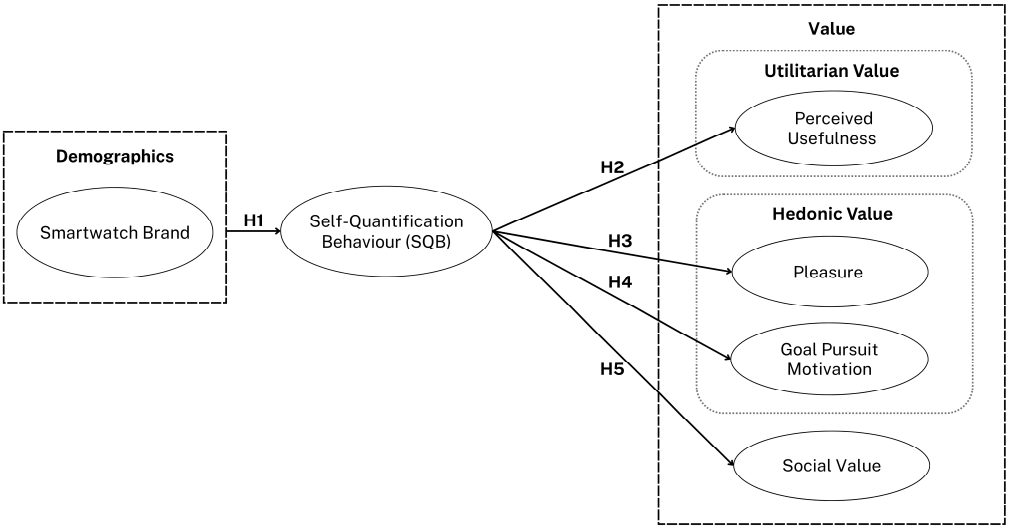


Figure 2. Research model and hypotheses.

Relevant constructs related to utilitarian, hedonic, and social value were selected for the model. Symbolic value was excluded, as it relates more to aspects of user self-expression and the perceptions of others [21], which fell outside the scope of physical well-being. The five hypotheses are as follows:

H1. *Smartwatch brand is positively associated with SQB.*

H2. *SQB is positively associated with PU.*

H3. *SQB is positively associated with pleasure.*

H4. *SQB is positively associated with GPM.*

H5. *SQB is positively associated with social value.*

4. Materials and Methods

The positivist approach of Saunders et al. [55] was employed in this study to address the research question, as it is particularly useful for explaining associations between variables using quantitative data. Through systematic measurement and hypothesis testing, this approach provides objective, reliable, and generalisable knowledge. Data collection was conducted using the survey approach with a questionnaire to test the developed hypotheses.

This approach was used because responses from a large population can easily be collected and analysed [56]. Data collection took place from June 2024 until September 2024.

4.1. Sampling and Recruitment of Participants

Two studies on PA and sedentary behaviour among office workers often generalised their findings despite the populations comprising individuals from various professions and industries [57,58]. Other studies have not included specific professions or industries, which has contributed to the lack of research related to the health and physical well-being of computing professionals [59]. The target population for the study was therefore computing professionals who used smartwatches. For this paper, the term computing professionals refers to those who work in the software development industry, such as software developers and project managers. This population was targeted because the industry is labour-intensive and typically deskbound, resulting in sedentary work. Extended sedentary periods and incorrect posture have led to many professionals developing severe musculoskeletal disorders [59].

Due to ethical approval restrictions at the research institution in South Africa where the authors are based, participants from other countries could not be included. The target population was therefore limited to South African smartwatch users. Purposive sampling was used to sample the target population. This method is a non-probability sampling technique that can be used for both qualitative and quantitative research [55,60]. A self-selection process, proposed by Saunders et al. [55], was employed, in which potential participant gatekeepers from various computing and software organisations were contacted via electronic communication platforms (i.e., mostly email) to obtain permission to distribute the call for participants to relevant employees in their organisations. This call contained: details about the study, the selection criteria, and a link to the Smartwatch Questionnaire, which was distributed to the gatekeepers of computing and software organisations and then shared by the gatekeepers with potential participants on internal organisational communication platforms, such as email or Slack channels. The selection criteria were as follows: (a) be between the ages of 18 and 65 years, (b) be South African, (c) work in the IT or software solution industry or department of an organisation, and (d) be able to understand, speak, and write in English.

Participants first self-identified in relation to the presented criteria and voluntarily offered to participate in the research. This process was chosen for this study because individuals are more likely to participate when they have a connection to the research and find it interesting, as indicated in the call for participants. The 2024 Research Edition of QuestionPro was used to create and distribute the Smartwatch Questionnaire. The questionnaire consisted of six sections. The first section covered demographic data, including the respondent's smartwatch brand. According to Laricchia [61], the five most popular smartwatch brands used by South Africans are Apple, Samsung, Huawei, Fitbit, and Garmin. The second section included statements related to the respondent's perceptions of smartwatch SQB. Each of the remaining four sections was related to the four constructs of value: PU, pleasure, GPM, and social value.

Each construct included related statements, and participants had to select a rating from a 5-point Likert scale, with 1 = Strongly Disagree and 5 = Strongly Agree. According to Kline [62], DeVellis [63] and Hair et al. [64], three well-developed items are often regarded as the minimum acceptable number for this purpose, provided they demonstrate satisfactory reliability and validity. Because the purpose of this paper is to gauge smartwatch users' perceptions, the full five-stage SQB Process for Smartwatches was not entirely applicable. Many of the autonomy stages take place 'behind the scenes' and are not visible to the user; therefore, survey participants could not offer feedback on each stage. Accordingly, not all

autonomy stages were represented in the instrument. With regard to the accuracy aspect of data collection, the assumption was made that the potential participants' smartwatches collect data that is accurate. Also, users lack an external benchmark for accuracy and therefore tend to trust their device data. Once the potential participants completed the self-selection process, the responses were compared with the presented criteria as a confirmation that they had read and met the criteria correctly. Potential participants who met all the criteria were enrolled in the study sample.

4.2. Validity and Reliability of Questionnaire, and Statistical Analysis Methods

The survey instrument was developed from established measures in the personal informatics and smartwatch CUI and value literature [7,10,18,21,65,66]. Content and face validity were ensured through a multi-step procedure: (1) item selection and adaptation from prior validated scales, (2) reviews by two domain experts (researchers in statistics and computing) to check clarity, relevance, and coverage of constructs (SQB, PU, pleasure, GPM, social value), and (3) a pilot test with a small convenience sample (n = 5) to identify and resolve any ambiguous wording and refine instructions. Finally, the survey administration procedures (standardised instructions, anonymous responses, and uniform data collection methods) that were used were selected to reduce measurement error and response bias. They also adhered to the ethics policy and rules of the authors' university.

The reliability of the Likert-scale questions was determined using Cronbach's alpha coefficient, and the internal consistency was interpreted from the resulting coefficient value [67]. The details are included in Table 1. A value of 0.80 or higher indicates excellent internal consistency among the scale items; values between 0.70 and 0.79 suggest good internal consistency; whilst values of 0.60 and 0.69 are considered fair. The reliability of SQB, pleasure, GPM, and social value was excellent. PU was the only variable with fair reliability. According to Suyidno et al. [67], all the constructs were considered reliable, as their coefficients were all greater than 0.60.

Table 1. Cronbach's alpha coefficients for the value constructs (n = 107).

Value Construct	Cronbach's Alpha Coefficient	Interpretation
SQB	0.87	Excellent
PU	0.67	Fair
Pleasure	0.91	Excellent
GPM	0.94	Excellent
Social Value	0.80	Excellent

Frequency distributions and other descriptive statistics, such as means, dispersion intervals in terms of Standard Deviations (SDs) and Confidence Intervals (CIs), were determined for each of the four value constructs. The questionnaire responses were statistically analysed using analysis of variance (ANOVA), a commonly used test for hypothesis testing. Cohen's d was used to determine the practical significance of the hypotheses, as it is a standardised effect size for calculating differences in mean values [68]. Cohen's d is the statistic used to determine the practical significance when the p-value is less than 0.05 for an inferential statistics test based on sample mean values, e.g., the t-test and Scheffé test. When the ANOVA results were statistically significant, post hoc ANOVA tests were conducted to determine specific group differences.

5. Results

Of the 126 submitted questionnaires, 19 were removed, as the respondents did not meet the criteria. Therefore, 107 responses were analysed. Due to space constraints, the frequency distributions for all the statements across all four value constructs are not included in the paper but are provided in Appendix A. Similarly, the detailed results of the ANOVA tests are included in Appendix B. The details are discussed in this section.

5.1. Participant Profile

Table 2 presents the participant profile, which shows that the majority of respondents were male and in the 25–34 age group. The most commonly owned smartwatch was Garmin (31%), followed by Apple (25%) and Samsung (18%). The Other group (15%) consisted of Huawei, Volkano, Polaroid, Honor, Xiaomi, Tom Tom, Whoop, and Polar smartwatch users. Only 11% of the participants used a Fitbit.

Table 2. Participant profile—South African computing professionals (n = 107).

Demographic	Category	*n*	%
Age (in years)	18–24	12	11%
	25–34	59	55%
	35–44	27	25%
	45–54	3	3%
	55–64	6	6%
	Total	107	100%
Gender	Female	34	32%
	Male	72	67%
	Other	1	1%
	Total	107	100%
Smartwatch Brand	Apple	27	25%
	Samsung	19	18%
	Fitbit	12	11%
	Garmin	33	31%
	Other	16	15%
	Total	107	100%

5.2. User Perceptions of Smartwatch SQB for PA

Table 3 presents the frequency distributions for each statement of SQB. It is clear from the table that the majority of the respondents Agreed with all three SQB statements. For SQB_1, the majority of respondents (58%) either Agreed (34%) or Strongly Agreed (24%) that they regularly checked or analysed their PA data collected by their smartwatches, whilst 21% had a Neutral response, and 21% either Disagreed (14%) or Strongly Disagreed (7%). For SQB_2, most respondents (71%) either Agreed (40%) or Strongly Agreed (31%) that collecting their PA data was important to them, 15% had a Neutral perception, while 8% Disagreed and 6% Strongly Disagreed. For SQB_3, the majority of respondents (70%) either Agreed (45%) or Strongly Agreed (25%) that they could make connections between their PA behaviour and the data collected on their smartwatches, whilst 19% indicated a Neutral perception, and 12% either Disagreed (6%) or Strongly Disagreed (6%).

Table 3. Frequency distributions—SQB (*n* = 107).

Statement	Strongly Disagree		Disagree		Neutral		Agree		Strongly Agree	
	n	**%**	***n***	**%**	***n***	**%**	***n***	**%**	***n***	**%**
SQB_1: I analyse/check my collected data regularly.	8	7%	15	14%	22	21%	36	34%	26	24%
SQB_2: It is important for me to collect data on my physical activity.	6	6%	9	8%	16	15%	43	40%	33	31%
SQB_3: I make connections between my physical activity behaviour and the data that I get from self-tracking devices.	6	6%	6	6%	20	19%	48	45%	27	25%

To analyse frequency distributions statistically, it is recommended to group Likert-type scale items into a statistical survey scale and calculate a total or mean score for each item [69]. Therefore, Table 4 summarises the frequency distributions for the SQB statements, classified into a five-point statistical scale, with the lower and upper mean values calculated and split into equal groups of 0.8 width. The resulting groups are: Very Negative ($\bar{x}$: 1.00 to 1.79), Negative ($\bar{x}$: 1.80 to 2.59), Neutral ($\bar{x}$: 2.60 to 3.40), Positive ($\bar{x}$: 3.41 to 4.20), and Very Positive ($\bar{x}$: 4.21 to 5.00). Each group maps to a response on the five-point Likert scale.

Table 4. Frequency distribution summary—SQB (*n* = 107).

Very Negative		Negative		Neutral		Positive		Very Positive	
($\bar{x}$: 1.00 to 1.79)		**($\bar{x}$: 1.80 to 2.59)**		**($\bar{x}$: 2.60 to 3.40)**		**($\bar{x}$: 3.41 to 4.20)**		**($\bar{x}$: 4.21 to 5.00)**	
n	%	*n*	%	*n*	%	*n*	%	*n*	%
6	6%	6	6%	26	24%	34	32%	35	33%

According to the frequency distribution scale, the majority (65%) of respondents expressed Very Positive (33%) and Positive (32%) perceptions towards SQB. Almost a quarter of respondents (24%) expressed a Neutral perception towards SQB, while 6% expressed a Negative perception and 6% a Very Negative perception.

Table 5 presents the aggregated mean, dispersion, and CIs for all three SQB statements. The aggregated mean of 3.71 indicated that most responses to all three SQB statements were perceived as Positive (95% CI), consistent with the frequency distributions in Table 3. The SD indicated moderate variability in the responses.

Table 5. Mean, dispersion and confidence intervals—SQB (*n* = 107).

Mean ($\bar{x}$)	SD	Minimum	Quartile 1 (Q1)	Median	Quartile 3 (Q3)	Maximum	95% CI Lo	95% CI Hi	CI Category
3.71	1.02	1.00	3.33	4.00	4.33	5.00	3.52	3.90	Positive

The 95% CI [3.52, 3.90] confirmed that the population mean was significantly above the neutral midpoint. While the full range of the scale was utilised (Min = 1.00, Max = 5.00), the interquartile range (IQR = 1.00) indicated that 50% of respondents scored between 3.33 (Q1) and 4.33 (Q3), suggesting a concentration of positive sentiment.

5.3. Descriptive Statistics and Frequency Distributions for All Value Constructs

Table 6 summarises the descriptive statistics for the aggregated scores of all four value constructs. PU reported the highest mean ($\bar{x}$ = 4.02, SD = 0.68), indicating that respondents, on average, viewed the system as useful. The relatively low SD suggests limited variability

in responses, implying a degree of consensus among participants. This is further supported by the interquartile range (Q1 = 3.67; Q3 = 4.33), which shows that the central 50% of responses were concentrated within the Positive range.

Table 6. Descriptive statistics: mean, SD and CIs—value constructs (*n* = 107).

Value Construct	Mean ($\bar{x}$)	SD	Minimum	Quartile 1 (Q1)	Median	Quartile 3 (Q3)	Maximum	95% CI Lo	95% CI Hi	CI Category
PU	4.02	0.68	1.00	3.67	4.00	4.33	5.00	3.89	4.15	Positive
Pleasure	3.87	0.77	1.00	3.33	4.00	4.17	5.00	3.72	4.02	Positive
GPM	3.78	1.03	1.00	3.17	4.00	4.67	5.00	3.58	3.98	Positive
Social Value	3.00	0.99	1.00	2.33	3.00	3.67	5.00	2.81	3.19	Neutral

The 95% confidence interval (CI: [3.52, 3.90]) fell entirely above the neutral midpoint, reinforcing the classification of this construct as positive. Pleasure also yielded a positive evaluation ($\bar{x}$ = 3.87, SD = 0.77), although slightly lower than PU. The median of 4.00 suggests that at least half of the respondents rated their experience positively. The spread of responses was moderate, as indicated by the SD and interquartile range (Q1 = 3.33; Q3 = 4.17). The 95% CI (3.72–4.02) remained above the Neutral threshold, confirming a generally positive response.

For GPM, the mean score ($\bar{x}$ = 3.78, SD = 1.03) indicates a positive but more varied perception. The higher SD compared to the other constructs suggests greater heterogeneity in responses. This is also reflected in the wider interquartile range (Q1 = 3.17; Q3 = 4.67). Although the 95% CI [3.58, 3.98] still fell within the Positive range, its proximity to the Neutral midpoint indicates that perceptions were less uniformly favourable than for PU and pleasure. Social value recorded a mean of 3.00 (SD = 0.99), corresponding exactly to the neutral midpoint of the scale. The median of 3.00 and interquartile range (Q1 = 2.33; Q3 = 3.67) further indicate a balanced distribution of responses around neutrality. The 95% CI [2.81, 3.19] values were both below and above the midpoint, suggesting no clear directional tendency in respondents' perceptions. These results support its classification as neutral.

Table 7 presents the aggregated frequency distributions for the four value constructs, providing additional insight into the polarity and dispersion of responses across them, complementing the descriptive statistics. For PU, responses were strongly skewed toward the positive end of the scale. A substantial majority of respondents rated PU as either Positive (37%) or Very Positive (43%), yielding a combined 80% favourable response rate. Only 2% of responses fell within the negative categories, while 18% were neutral. This distribution indicates a clear consensus on the usefulness of smartwatches, with minimal dissent.

Table 7. Frequency distribution summary—value constructs (*n* = 107).

Value Construct	Very Negative ($\bar{x}$: 1.00 to 1.79)		Negative ($\bar{x}$: 1.80 to 2.59)		Neutral ($\bar{x}$: 2.60 to 3.40)		Positive ($\bar{x}$: 3.41 to 4.20)		Very Positive ($\bar{x}$: 4.21 to 5.00)	
PU	1	1%	1	1%	19	18%	40	37%	46	43%
Pleasure	2	2%	1	1%	26	24%	51	48%	27	25%
GPM	5	5%	9	8%	23	21%	31	29%	39	36%
Social Value	12	11%	21	20%	44	41%	19	18%	11	10%

A similar pattern was observed for pleasure, although with slightly less intensity. The majority of responses were Positive (48%) or Very Positive (25%), resulting

in 73% favourable ratings overall. Neutral responses accounted for 24%, while Negative and Very Negative responses remained negligible (3% combined). This suggests that most participants found the system enjoyable, though with a slightly broader range of perceptions than in PU.

For GPM, responses were strongly skewed toward the Very Positive end of the scale. A substantial majority of respondents rated GPM as Very Positive (36%) and Positive (29%), which yielded a combined 65% favourable response rate. Only 13% of responses fell within the negative categories, while 21% were neutral. This distribution indicates a clear consensus on the role of smartwatches in motivating the respondents to achieve their PA goals.

For social value, responses were strongly concentrated around the midpoint, with mostly Neutral responses (41%), suggesting indifference towards smartwatch social features amongst the respondents. The percentages of Negative (20%) and Positive (18%) responses were similar, differing by only 2%. A similar trend was observed between the Very Negative (11%) and Very Positive (10%) responses, yielding a negligible 1% difference at the two extreme ends of the scale. Overall, the responses indicate a pronounced central tendency with slight asymmetry, suggesting that most respondents did not have strong opinions towards the social value of smartwatches.

5.4. H1: The Association Between Smartwatch Brand and SQB

Respondents were asked which smartwatch brand they used, and these responses were analysed alongside each respondent's three SQB statement responses. Table 8 summarises the descriptive statistics related to SQB by smartwatch brand.

Table 8. Descriptive statistics—SQB by smartwatch brand (n = 107).

Group	All	Apple	Fitbit	Garmin	Samsung	Other
n	107	27	12	33	19	16
SQB Mean ($\bar{x}$)	3.71	3.78	3.50	3.94	3.56	3.48
SD	1.02	1.03	0.77	1.05	1.00	1.12
95% CI low	3.52	3.37	3.01	3.57	3.08	2.88
95% CI high	3.91	4.18	3.99	4.31	4.04	4.08

The Garmin respondents had the highest mean SQB score ($\bar{x}$ = 3.94) among all smartwatch brands, suggesting the highest level of SQB. The Apple respondents had the second-highest mean SQB score ($\bar{x}$ = 3.78), which was higher than the overall mean ($\bar{x}$ = 3.71). The mean values of SQB for the Samsung ($\bar{x}$ = 3.56), Fitbit ($\bar{x}$ = 3.50), and Other ($\bar{x}$ = 3.48) respondents were lower than the overall mean ($\bar{x}$ = 3.71), which suggested that these respondents had a lower SQB compared to the average population. The Other respondents had the lowest mean value, which could be due to this category comprising a variety of smartwatch brands or to the lower accuracy of these devices, leading to decreased usage. The 95% CI range for the mean was [3.52, 3.91]. These results indicate a positive overall evaluation of service quality beliefs, with the narrow confidence interval confirming the precision of the mean estimate despite the moderate variability in individual responses.

The one-way ANOVA examining SQB across smartwatch brands indicated that brand does not have a statistically significant association with SQB (see Appendix B). The results showed that the between-group variability (SS = 3.67, df = 4, MS = 0.92) was smaller than the within-group variability (SS = 106.03, df = 102, MS = 1.04). This relationship was reflected in the F-statistic (F(4, 102) = 0.88), which was below 1, indicating that differences between smartwatch brands were minimal relative to the variability observed within each brand

group. The *p*-value ($p = 0.477$) was substantially higher than the conventional significance level of 0.05. Consequently, the null hypothesis, that the mean SQB was equal across all smartwatch brands, cannot be rejected. This suggests that any observed differences in SQB scores between brands were likely due to random variation rather than systematic brand-related effects. Therefore, the hypothesis H1 was not supported. However, these results are interesting, as it was expected that SQB would differ among users of different smartwatch brands, since the sensors and functions available for each brand differ.

5.5. H2: The Association Between Smartwatch SQB and PU

The frequency distributions for PU showed that the majority of respondents Agreed with the respective statements: PU_1 '*Using my smartwatch is useful to me*' (50%), PU_2 '*Using my smartwatch keeps me happy*' (36%), and PU_3 '*Using my smartwatch is enjoyable to me*' (54%). The aggregated frequency distributions for all three statements showed that most responses (43%) were Very Positive. The descriptive statistics in Table 6 confirmed this result, as the aggregated mean across all three statements ($\bar{x} = 4.02$) fell within the Positive CI range, indicating that respondents had a positive perception of the PU of their smartwatches.

Table 9 presents the descriptive statistics for PU analysed by SQB group. The SQB groups were calculated by analysing the Likert-scale responses for SQB and classifying them into three groups: Lower SQB (<Q1), Middle SQB (Q1–Q3), and Higher SQB (>Q3). The Lower SQB group showed responses lower than Q1 ($\bar{x} = 3.33$); the Middle SQB group was in the middle range between Q1 and Q3 ($3.33 < \bar{x} < 4.60$); and the Higher SQB group included responses higher than Q3 ($\bar{x} = 4.60$).

Table 9. Descriptive statistics—Perceived Usefulness (PU) by SQB.

Group	All	Lower SQB (<Q1)	Middle SQB (Q1–Q3)	Higher SQB (>Q3)
n	107	24	58	25
PU Mean ($\bar{x}$)	4.02	3.33	4.05	4.60
SD	0.68	0.71	0.47	0.45
95% CI low	3.89	3.03	3.93	4.41
95% CI high	4.15	3.63	4.18	4.79

The Higher SQB group had the highest PU mean ($\bar{x} = 4.60$), indicating that respondents who had a higher SQB experienced the highest PU. Those in the Middle SQB group reported a higher level of PU ($\bar{x} = 4.05$) than the sample average ($\bar{x} = 4.02$), whilst respondents in the Lower SQB group experienced a PU ($\bar{x} = 3.33$) below the sample average.

The PU score yielded a mean of 4.02 (SD = 0.68). The 95% CI for the aggregated mean ranged from 3.89 to 4.15, suggesting that the population average likely falls within this narrow range and indicating high precision in the estimate.

One-way ANOVA was conducted to examine differences in PU across SQB groups. The results revealed a statistically significant association between SQB and PU ($F(2, 104) = 35.42$, $p < 0.0005$). This indicated that mean PU scores differed significantly between SQB groups. The *p*-value ($p < 0.0005$) was far below the conventional significance threshold of 0.05, leading to rejection of the null hypothesis that all group means are equal. This provides strong evidence that PU differs significantly across SQB levels. Therefore, H2 was supported, and post hoc tests were conducted to determine which SQB groups differed. The summarised results of these tests are provided in Table 10, and show that there were statistically and practically significant differences between the following groups:

- The Lower and Middle SQB groups;
- The Lower and Higher SQB groups;

- The Middle and Higher SQB groups.

Table 10. Post hoc tests for ANOVA—PU by SQB.

SQB Group 1	SQB Group 2	Diff. M_1-M_2	Scheffé *p*	Cohen's d	
Lower (<Q1)	Middle (Q1–Q3)	−0.72	<0.0005	1.31	Large
Lower (<Q1)	Higher (>Q3)	−1.27	<0.0005	2.14	Large
Middle (Q1–Q3)	Higher (>Q3)	−0.55	<0.0005	1.18	Large

The Middle SQB group experienced more PU due to moderate SQB levels compared to the Lower SQB group (M_1-M_2= −0.72; $p < 0.0005$; Cohen's d = 1.31, Large). The Higher SQB group also experienced higher PU levels than the Lower group (M_1-M_2= −1.27; $p < 0.0005$; Cohen's d = 2.14 Large) and the Middle SQB group (M_1-M_2 = −0.55; $p < 0.0005$; Cohen's d = 1.18 Large). All three post hoc tests indicated a large effect size for PU between the SQB groups, suggesting that the differences in PU across the SQB groups are both statistically and practically meaningful.

5.6. H3: The Association Between Smartwatch SQB and Pleasure

The frequency distribution results showed that for the three pleasure statements, the majority of the respondents Agreed with statements PL_1 '*Using my smartwatch is fun to me*' (48%) and PL_3 '*Using my smartwatch is enjoyable to me*' (56%). However, for PL_2 '*Using my smartwatch keeps me happy*', the respondents were mostly Neutral (39%). These results align with the descriptive statistics in Table 6, showing that the aggregated mean for all three pleasure statements was Positive.

The descriptive statistics for pleasure by SQB are presented in Table 11. The Higher SQB group had the highest mean ($\bar{x}$ = 4.13) for pleasure, indicating that respondents who had a higher SQB level experienced the greatest pleasure. The Middle SQB group had the second-highest mean ($\bar{x}$ = 4.06) among the groups. Both the Higher SQB group and the Middle group reported a higher level of pleasure than the aggregated mean ($\bar{x}$ = 3.87). The respondents in the Lower SQB group reported a Neutral level of pleasure ($\bar{x}$ = 3.15), which was lower than the sample average. The 95% CI range for the mean was [3.72, 4.02]. This narrow interval suggests high precision in the estimate of the population mean, indicating that the true average level of pleasure in the broader population likely falls within this range.

Table 11. Descriptive statistics—pleasure by SQB.

Group	All	Lower SQB (<Q1)	Middle SQB (Q1–Q3)	Higher SQB (>Q3)
n	107	24	58	25
Pleasure Mean ($\bar{x}$)	3.87	3.15	4.06	4.13
SD	0.77	0.86	0.55	0.73
95% CI low	3.72	2.79	3.91	3.83
95% CI high	4.02	3.52	4.20	4.44

One-way ANOVA was conducted to examine differences in pleasure across SQB groups. The results showed a statistically significant association ($F(2, 104) = 17.69$, $p < 0.0005$). Since the *p*-value ($p < 0.0005$) was well below the conventional alpha level

of 0.05, it indicates that mean pleasure scores varied significantly between SQB groups. Therefore, the hypothesis H3, that SQB affects pleasure, was supported, and post hoc tests (Table 12) were conducted. These test results revealed that there were statistically significant differences between the following groups:

- The Lower and Middle SQB groups;
- The Lower and Higher SQB groups.

Table 12. Post hoc tests for ANOVA—pleasure by SQB.

SQB Group 1	SQB Group 2	Diff. M_1-M_2	Scheffé *p*	Cohen's d	
Lower (<Q1)	Middle (Q1–Q3)	−0.90	<0.0005	1.38	Large
Lower (<Q1)	Higher (>Q3)	−0.98	<0.0005	1.23	Large
Middle (Q1–Q3)	Higher (>Q3)	−0.08	0.897	0.12	Not sig

The Middle SQB group experienced more pleasure than the Lower SQB group due to higher SQB levels (M_1-M_2 = −0.90; $p < 0.0005$; Cohen's d = 1.38, Large). The same trend was observed between the Lower and Higher SQB group, where the Higher SQB group experienced more pleasure than the Lower SQB group due to higher SQB levels (M_1-M_2= −0.98; $p < 0.0005$; Cohen's d = 1.23, Large). Both results indicated a large effect size between the groups on pleasure, suggesting that the differences in pleasure across the SQB groups are both statistically and practically meaningful.

5.7. H4: The Association Between Smartwatch SQB and GPM

The frequency distributions for the three statements of GPM showed that the respondents Agreed with statements GPM_1 '*Using my smartwatch motivates me to work towards a healthier lifestyle*' (41%), and GPM_2 '*Using my smartwatch keeps me motivated to exercise regularly*' (35%). They Strongly Agreed with the statement GPM_3 '*Using my smartwatch pushes me to increase the effort I put towards exercising*' (34%). These results align with those in Table 6, where the aggregated mean of 3.78 for GPM indicates that respondents had a Positive perception of the smartwatch as a motivator for pursuing their goals.

Table 13 presents the descriptive statistics for GPM by SQB. The Higher SQB group had the highest mean ($\bar{x}$ = 4.44), indicating that respondents with higher SQB levels had the highest GPM. For the Middle SQB group, the respondents had a Positive perception of GPM ($\bar{x}$ = 3.80), which was higher than the study average ($\bar{x}$ = 3.78). Respondents in the Lower SQB group had Neutral GPM ($\bar{x}$ = 3.03). The 95% CI range for the mean was [3.58, 3.98]. Although the SD suggests a moderate degree of variance in participant responses, the narrow CI indicated that the sample mean remains a precise estimate of the population average.

Table 13. Descriptive statistics—GPM by SQB.

Group	All	Lower SQB (<Q1)	Middle SQB (Q1–Q3)	Higher SQB (>Q3)
n	107	24	58	25
GPM Mean ($\bar{x}$)	3.78	3.03	3.80	4.44
SD	1.03	1.08	0.92	0.74
95% CI low	3.58	2.57	3.56	4.14
95% CI high	3.98	3.48	4.05	4.74

One-way ANOVA was conducted to examine differences in GPM across the SQB groups. The results revealed a statistically significant association ($F(2, 104) = 14.47$, $p < 0.0005$), indicating that the mean GPM scores differed significantly between the SQB groups. The p-value ($p < 0.0005$) was well below the conventional significance threshold of 0.05, providing support for hypothesis H4. These findings suggest that SQB is significantly associated with GPM, with respondents in different SQB categories reporting meaningfully different perceptions. However, compared to earlier results (e.g., PU), the relatively larger within-group variance indicated somewhat greater dispersion in responses, suggesting that while the association was significant, perceptions of GPM were more varied within groups. Due to the significant ANOVA results, post hoc tests (Table 14) were conducted, and it was determined that there were statistically significant differences between the groups for the following three cases:

- The Lower and Middle SQB groups;
- The Lower and Higher SQB groups;
- The Middle and Higher SQB groups.

Table 14. Post hoc tests for ANOVA—GPM by SQB.

SQB Group 1	SQB Group 2	Diff. M_1-M_2	Scheffé p	Cohen's d	
Lower (<Q1)	Middle (Q1–Q3)	−0.78	0.003	0.80	Large
Lower (<Q1)	Higher (>Q3)	−1.41	<0.0005	1.53	Large
Middle (Q1–Q3)	Higher (>Q3)	−0.64	0.018	0.73	Medium

The Middle SQB group experienced more GPM due to moderate SQB levels compared to the Lower SQB group (M_1-$M_2 = -0.78$; $p = 0.003$; Cohen's d = 0.80, Large).

In the last two cases, the Higher SQB group experienced higher levels of GPM than the Lower SQB group (M_1-$M_2 = -1.41$; $p < 0.0005$; Cohen's d = 1.53 Large) and the Middle group (M_1-$M_2 = -0.64$; $p = 0.018$; Cohen's d = 0.73 Medium). The Lower and Middle SQB groups (Cohen's d = 0.80) and the Lower and Higher SQB groups (Cohen's d = 1.53) had large effect sizes, indicating that the differences in GPM across SQB groups are both statistically and practically meaningful.

5.8. H5: The Association Between Smartwatch SQB and Social Value

The respondents Disagreed with statements SV_1 '*I like using my smartwatch for sharing my activity progress with others*' (29%) and SV_2 '*Sharing my progress with others helps to keep me motivated*' (31%). However, they Agreed with the statement SV_3 '*Using this smartwatch supports my lifestyle*' (52%). The mean for social value ($\bar{x} = 3.00$) in Table 6 aligns with these results, indicating that respondents had a Neutral perception of the social value of their smartwatches.

Table 15 presents the descriptive statistics of social value by SQB. The responses with the highest mean ($\bar{x} = 3.61$) were from the Higher SQB group, indicating that respondents with higher SQB levels experienced the highest social value. For the Middle SQB group, the respondents had Neutral perceptions ($\bar{x} = 3.03$) towards social value. Respondents in the Lower SQB group reported low social value ($\bar{x} = 2.28$). The 95% CI for the mean ranged from 2.81 to 3.19. Notably, the interval includes the scale's neutral midpoint, indicating that the sample does not lean significantly toward either a positive or negative perception of social value.

Table 15. Descriptive statistics—social value by SQB.

Group	All	Lower SQB (<Q1)	Middle SQB (Q1–Q3)	Higher SQB (>Q3)
n	107	24	58	25
Social Value Mean ($\bar{x}$)	3.00	2.28	3.03	3.61
SD	0.99	0.89	0.81	1.04
95% CI low	2.81	1.90	2.82	3.18
95% CI high	3.19	2.65	3.25	4.04

One-way ANOVA was conducted to examine differences in social value across the SQB groups. The results showed a statistically significant association between SQB and social value ($F(2, 104) = 14.11$, $p < 0.0005$), since the p-value was well below the conventional threshold of 0.05, leading to rejection of the null hypothesis. This confirms that the mean social value differs significantly across SQB groups and H5 can be accepted. Therefore, post hoc tests (Table 16) were conducted to determine which groups differed significantly. There were statistically significant differences between the groups for the following three cases:

- The Lower and Middle SQB groups;
- The Lower and Higher SQB groups;
- The Middle and Higher SQB groups.

Table 16. Post hoc tests for ANOVA—social value by SQB.

SQB Group 1	SQB Group 2	Diff. M_1-M_2	Scheffé p	Cohen's d	
Lower (<Q1)	Middle (Q1–Q3)	−0.76	0.003	0.91	Large
Lower (<Q1)	Higher (>Q3)	−1.34	<0.0005	1.38	Large
Middle (Q1–Q3)	Higher (>Q3)	−0.58	0.027	0.66	Medium

The Middle SQB group showed greater social value than the Lower SQB group, a difference associated with higher SQB levels (M1-M2 = −0.76). In the last two cases, the Higher SQB group reported higher levels of social value than both the Lower SQB group (M1-M2 = −1.34) and the Middle SQB group (M1-M2 = −0.58). The Lower and Middle SQB groups (Cohen's d = 0.91) and the Lower and Higher SQB groups (Cohen's d = 1.38) had large effect sizes, indicating that the differences in social value across SQB groups are both statistically and practically meaningful.

6. Discussion

6.1. RQ1: What Are Users' Perceptions of Smartwatch SQB?

The personal informatics systems model of Li et al. [34] was extended to the SQB process for smartwatches presented in this paper (Figure 1), since a smartwatch can be classified as a personal informatics system that enables self-tracking, also known as self-quantification, or SQB. The five stages of SQB, from data preparation and collection to user reflections, were classified into two main phases: autonomy and user–smartwatch interaction. The activities and features offered by various smartwatch brands in these phases can vary. Based on the literature, a model of the associations between smartwatch brand, SQB and value was developed (Figure 2), and a survey was conducted to test and validate the model. The respondents were 107 office workers in South Africa whose jobs were mostly desk-bound, which usually increases sedentary behaviour during office hours,

negatively affecting physical movement and good health and fitness. They were mostly male and young (age group 35–44). The most popular smartwatch brand among these respondents was Garmin, followed by Apple, both of which, according to Laricchia [61], are the most popular brands among South Africans.

The findings indicated that the respondents' overall perceptions of SQB were positive. They reported regularly collecting/analysing their PA data on their smartwatches, finding it important to collect it, and being able to make a mental connection between their PA behaviour and the collected data. When SQB was analysed by smartwatch brand, the findings indicate that SQB was relatively consistent across brands, with no evidence that any brand produced SQB that was significantly higher or lower than the others. In practical terms, the smartwatch brand is not associated with SQB in this sample. Therefore, the hypothesis H1 is not supported. This result is unexpected, as Kim [70] and Bekker and Scholtz [71] showed that SQB features can differ across users of different smartwatch brands, since each brand and model can offer variations in sensors and functions. Additionally, the report by Dhar and Wertenbroch [20] found that purchasing decisions across products are influenced by the hedonic and utilitarian value of goods.

6.2. RQ2: How Does SQB Affect the Perceived Value of Smartwatches?

More than half of the respondents agreed that their smartwatch was useful, and they could navigate to find relevant information quickly and easily, whilst to a lesser extent, just over a third found that it increased their physical productivity. Overall, most responses were very positive towards PU. PU was also the most highly rated of the four value constructs. This finding highlights that utility is a key driver of smartwatch usage.

The findings also indicated that higher levels of SQB in the sample were associated with stronger perceptions of smartwatch usefulness (PU). Respondents with higher SQB levels reported significantly higher PU than those with lower SQB, highlighting the importance of behavioural interactions in shaping utility perceptions. The largest practically significant difference was observed between the lower and higher SQB groups, suggesting that the association between SQB and PU becomes more pronounced in the higher SQB group than in the lower SQB group, consistent with the threshold effect highlighted by Lewis-Beck et al. [72]. This result is consistent with the observation that, in this sample, perceptions of usefulness were higher among users who reported a greater level of interaction with a smartwatch. The support for hypothesis H2, therefore, confirms that SQB is significantly associated with PU, consistent with the findings of Siepmann and Kowalczuk [18]. These findings suggest that sustained and meaningful engagement with smartwatch features is necessary for users to fully recognise their functional value.

Regarding hedonic value, the findings suggest that respondents generally perceived smartwatch use as a pleasurable experience. Pleasure ranked second among the value constructs for the respondents, and overall, they were positive about the pleasure they experienced from using their smartwatches. However, whilst most respondents reported that their smartwatch was perceived as fun and enjoyable, a notable proportion remained neutral about its contribution to their feelings of happiness, suggesting some variability in affective outcomes. Beyond these descriptive insights, the analysis indicates that SQB had a statistically significant association with perceived pleasure, with significant differences in affective responses across the SQB groups. More specifically, respondents with lower levels of SQB reported significantly less pleasure than those with moderate or high SQB. The largest practically significant difference was observed between the lower and middle SQB groups, indicating that, in this sample, pleasure was associated with SQB such that the middle group reported notably higher pleasure than the lower group. In contrast, the absence of a practically significant difference between the two highest SQB groups suggests

that, beyond moderate SQB, the association between SQB and pleasure becomes negligible. The support for H3, therefore, indicates that those with higher SQB reported greater perceived pleasure, albeit with a plateau effect at higher levels. This finding is consistent with prior research by Jung and Kang [73] and Beh et al. [74], which found that users derive enjoyment from interacting with smartwatches, particularly when these devices enable continuous monitoring of physiological data such as PA. Overall, these results underscore the role of behavioural engagement in shaping positive affective experiences with smartwatch use.

With reference to the second construct of hedonic value, namely GPM, the descriptive results indicate that the respondents generally held positive perceptions of GPM regarding their use of smartwatches. Just over a third of respondents perceived a connection between their smartwatch and greater exercise effort, as reflected in their strong agreement with statements attributing motivational influence on the device. Respondents mostly agreed with the other two GPM-related statements, stating that their smartwatches helped them remain consistently motivated to exercise and adopt a healthy lifestyle, suggesting an overall favourable motivational effect. Beyond these descriptive patterns, the analysis demonstrates that SQB was significantly associated with GPM, providing support for H4 and aligning with prior findings by Siepmann and Kowalczuk [18]. Respondents in different SQB groups reported meaningfully different perceptions. Respondents with moderate and high levels of SQB reported greater motivation to pursue PA goals than those with low levels of SQB. The largest practically significant difference was observed between the lower and higher SQB groups, suggesting that the most pronounced difference in motivation is associated with these extremes. Notably, even moderate levels of SQB were associated with significantly higher GPM, suggesting that relatively higher SQB corresponds to meaningful differences in motivation. Although motivation is higher among those with high SQB compared to those with moderate SQB, the smaller effect size between these groups indicates a diminishing incremental difference in motivation relative to the differences observed between lower and moderate levels, and between lower and higher levels. Furthermore, the relatively greater within-group variance suggests greater dispersion in GPM responses, indicating that while SQB was significantly associated with motivation, individual perceptions of GPM were more heterogeneous than those for other constructs, such as PU.

Regarding social value, the descriptive findings suggest a mixed but generally positive perception of it associated with smartwatch use. While just over half of the respondents agreed that their smartwatch supported their lifestyle, a notable proportion expressed negative views regarding socially oriented features. Specifically, just under a third disagreed that they enjoyed sharing the progress of their activities, and a similar proportion indicated that such sharing did not enhance their motivation. According to Epstein [44], smartwatch users use data-sharing features to present a favourable image of themselves to others. However, the proportion of negative responses could signal that many respondents may choose not to engage with data-sharing features due to the possibility of scrutiny from others and possibly lower PA levels. Despite these reservations, overall perceptions of social value remained largely positive. These results are consistent with those of Asimakopoulos et al. [6] and Pennington and Dam [54], who found that social interaction and data sharing among smartwatch users positively impact users' PA engagement, device interaction, and CUI, which relate to perceived value.

The inferential results indicated that SQB was significantly associated with perceived social value, providing support for H5. Although social value is inherently more context-dependent and socially constructed than constructs such as PU or pleasure, the findings demonstrate that it varies systematically across SQB groups. This result suggests that

differences in behavioural (or SQB) levels are associated with meaningful shifts in users' perceptions of social benefit and social image. More specifically, respondents with lower SQB levels reported lower social value than those with moderate or high SQB. The largest practically significant difference was observed between the lower and higher SQB groups, suggesting that the most pronounced difference in perceived social value is associated with these extremes. Furthermore, even moderate levels of SQB were associated with significantly higher social value. While social value is higher among those with high SQB compared to those with moderate SQB, the smaller effect size between these groups suggests a diminishing incremental difference in social value at higher SQB levels. Overall, these findings suggest that SQB is significantly associated with perceived social value, albeit with greater variability reflecting the socially contingent nature of the construct.

6.3. Updated Research Model

Figure 3 illustrates the updated model. Since H1 was not supported, the smartwatch brand is no longer included in the model. The other four hypotheses were supported, indicating that as the level of SQB rises, the more the respondents found smartwatches useful, enjoyed using them, and were motivated to pursue their fitness goals. SQB also affected the social value they experienced, albeit to a lesser extent.

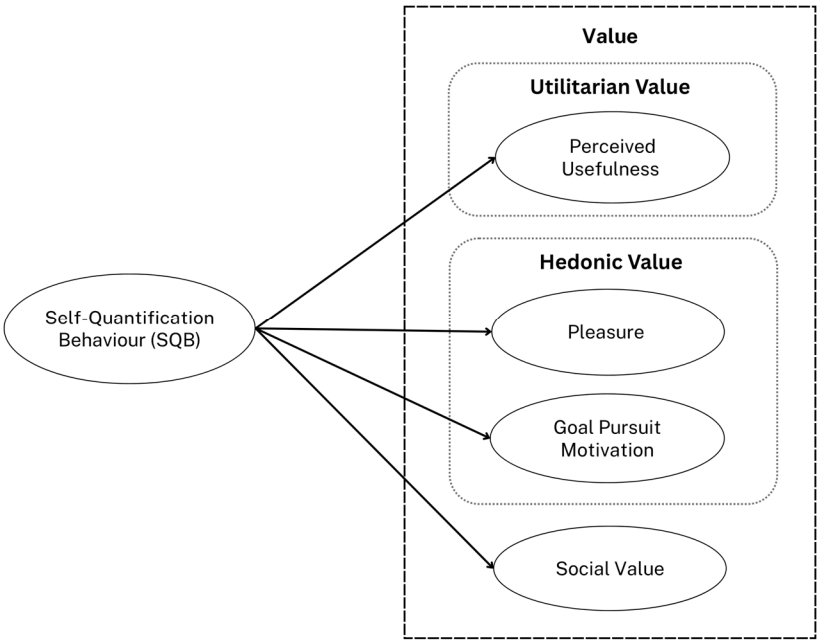


Figure 3. Updated research model: smartwatch SQB associations with value.

The study met the requirements for validity and reliability. Content and face validity of the questionnaire were ensured through a multiple-step approach that included an expert review and a pilot test. The survey administration procedures followed ethical guidelines and aimed at reducing measurement error and response bias.

6.4. Limitations and Future Work

A limitation of the study was the slightly skewed sample, which was mostly young male smartwatch users. The respondents in this study were also recruited through self-selection and had to own or use a smartwatch, which could indicate a pre-existing interest in health and thereby introduce potential bias into the study. The research was also limited by the number of smartwatch brands used by the participants, to reduce the effort of integrating data from hundreds of smartwatch brands. Another limitation of this paper is that only computing professionals in South Africa were included in the target population.

While the study's design limitations limit broad generalisability, it offers meaningful, contextually grounded insights. The use of a convenience sample, largely comprising younger male computing professionals within a single national context, enables a focused examination of smartwatch use within a relevant and increasingly influential user group. As the respondents were active smartwatch users, the findings provide direct insight into the behaviours and perceptions among engaged adopters, which is valuable for understanding real-world usage patterns. Although the cross-sectional design limits causal inference, the results identify important associations and areas of variability (e.g., in social value) that can inform theory development and guide future hypothesis testing.

Future research could extend the study through replication in more diverse populations, as well as through longitudinal and experimental approaches to further interrogate causal mechanisms, behavioural change over time, and the effectiveness of specific device features and intervention strategies in promoting sustained SQB and related health outcomes. In addition, other studies could investigate larger sample sizes in other contexts and countries. For example, research could replicate the study among other sedentary professions to identify new and similar trends. It is also recommended that the association between smart device functions and SQB should be investigated. Further research could examine additional constructs to identify and test their impact on the four suggested value constructs for maintaining and improving PA.

6.5. Research Contributions

The paper contributes to the field of personal informatics and self-quantification, in which self-quantified users collect PA data about themselves to support self-reflection. It addresses the gap identified in Cho et al. [10] regarding the lack of research on users' perceptions of smartwatch value. Understanding the value of smartwatches could guide manufacturers in designing these devices to motivate and encourage users to increase movement, thereby reducing sedentary behaviour and the risks of illnesses and non-communicable diseases associated with it. In companies, reducing sedentary behaviour by encouraging PA can improve employee health and productivity and reduce absenteeism due to ill health.

7. Conclusions

This study extended the personal informatics systems model to examine smartwatch SQB and its effects on perceived value among office-based smartwatch users in South Africa. Using survey data from 107 respondents, we found that overall SQB was positive and broadly consistent across smartwatch brands; therefore, brand was not significantly associated with SQB in this sample. Higher levels of SQB were associated with higher PU, pleasure, GPM, and perceived social value, with the most significant relationship observed for PU and GPM. Notably, several relationships exhibited threshold or diminishing-return patterns: usefulness was markedly higher among those who had reached a sufficient level of SQB compared to those below it, pleasure differed most between the low and moderate SQB groups, and social and motivational gains showed smaller incremental differences at higher SQB levels. Overall, the results suggest that the respondents perceived smartwatches as useful, enjoyable, and moderately valuable in terms of GPM, while their social value remained ambiguous. The relatively narrow confidence intervals for PU and pleasure indicate stable estimates, whereas the wider dispersion observed for GPM and social value suggests more diverse user experiences.

This paper provides three main contributions: (1) the SQB process for smartwatches (Figure 1), (2) a model of the factors influencing the perceived value of smartwatches (Figure 3), and (3) the application of these models to smartwatch users in South Africa. It

fills the gap in the limited publicly accessible, peer-reviewed data on smartwatch brand usage specifically in South Africa. Whilst there is some detailed market data from paid industry reports (e.g., International Data Corporation and Canalys), these are not freely accessible. Reports or articles that are available often mix smartphones and smartwatches or focus on niche segments such as cyclists or runners or lack methodological transparency.

The findings of this paper have three primary implications. Theoretically, they reinforce the central role of behavioural engagement in shaping multiple dimensions of product value within personal informatics frameworks. Practically, they suggest that designers and manufacturers should prioritise features and onboarding strategies that foster sustained, meaningful SQB, given its strong association with higher perceptions of usefulness and motivation, while recognising that incremental hedonic or social gains may plateau. For organisations, facilitating employees' use of smartwatch self-tracking may support PA goals and associated well-being benefits.

The study fills a gap in understanding how data collected from users and managed by smartwatches can transform human behaviour in ways that positively affect their health. Understanding the impact that SQB can have on the value that smartwatch users experience can benefit users themselves, smartwatch manufacturers, and researchers. Smartwatch users gain more insights into their PA and can adjust their SQB accordingly to maximise the value they get from their devices. Smartwatch manufacturers can use the results of this paper to conduct focus groups and possibly identify techniques to promote SQB and PA through smartwatch and companion mobile app functions. Researchers can benefit from this paper's findings by gaining a deeper understanding of smartwatch value, which could serve as a basis for further research and analysis. In summary, this study demonstrates that engagement in smartwatch self-quantification meaningfully shapes users' perceptions of device value—particularly usefulness and motivation—and highlights the importance of fostering adequate levels of behavioural interaction to realise the functional and motivational benefits of wearable personal informatics.

Author Contributions: Conceptualisation, C.B., B.M.S. and S.B.; methodology, C.B. and B.M.S.; software, C.B.; validation, C.B., B.M.S. and S.B.; formal analysis, C.B., B.M.S. and S.B.; investigation, C.B., B.M.S. and S.B.; resources, C.B., B.M.S. and S.B.; data curation, C.B.; writing—original draft preparation, C.B. and B.M.S.; writing—review and editing, C.B., B.M.S. and S.B.; visualisation, C.B.; supervision, B.M.S. and S.B.; project administration, C.B., B.M.S. and S.B.; funding acquisition, C.B. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Nelson Mandela University's Postgraduate Research Scholarships (PGRS), grant number S220105464.

Institutional Review Board Statement: The study was conducted in accordance with the Declaration of Helsinki and approved by the Research Ethics Committee: Human (REC-H) of Nelson Mandela University (protocol code 2024-SCI-0482, approval date: 19 March 2024).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study. Written informed consent was obtained from the participants to publish this paper.

Data Availability Statement: Participant data access is unavailable due to privacy and/or ethical restrictions.

Acknowledgments: We would like to thank Danie Venter for conducting the statistical analysis. During the preparation of this study, the author(s) used Grammarly (version 14.1282.0) for the purposes of grammar checking. The authors have reviewed and edited the output and take full responsibility for the content of this publication.

Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

PA	Physical Activity
SQB	Self-Quantification Behaviour
PU	Perceived Usefulness
GPM	Goal Pursuit Motivation
LED	Light-Emitting Diode
RAM	Random Access Memory
CSV	Comma-Separated Values
JSON	JavaScript Object Notation
XML	eXtensible Markup Language
CUI	Continuous Usage Intention
WHO	World Health Organization
SD	Standard Deviation
CI	Confidence Interval
ANOVA	Analysis of Variance
Q1	Quartile 1
Q3	Quartile 3

Appendix A. Frequency Distributions

Frequency distributions—PU (n = 107)

Statement	Strongly Disagree		Disagree		Neutral		Agree		Strongly Agree	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
PU_1: Using my smartwatch is useful to me.	1	1%	1	1%	7	7%	53	50%	45	42%
PU_2: Using the smartwatch increases my physical productivity.	4	4%	7	7%	25	23%	39	36%	32	30%
PU_3: Using my smartwatch allows me to navigate relevant information quickly and easily.	1	1%	5	5%	19	18%	58	54%	24	22%

Frequency distributions—pleasure (n = 107)

Statement	Strongly Disagree		Disagree		Neutral		Agree		Strongly Agree	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
PL_1: Using my smartwatch is fun to me.	2	2%	2	2%	18	17%	51	48%	34	32%
PL_2: Using my smartwatch keeps me happy.	2	2%	4	4%	42	39%	40	37%	19	18%
PL_3: Using my smartwatch is enjoyable to me.	2	2%	1	1%	23	21%	60	56%	21	20%

Frequency distributions—GPM (n = 107)

Statement	Strongly Disagree		Disagree		Neutral		Agree		Strongly Agree	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
GPM_1: Using my smartwatch motivates me to work towards a healthier lifestyle.	3	3%	7	7%	21	20%	44	41%	32	30%
GPM_2: Using my smartwatch keeps me motivated to exercise regularly.	4	4%	13	12%	25	23%	37	35%	28	26%
GPM_3: Using my smartwatch pushes me to increase the effort I put toward exercising.	6	6%	9	8%	24	22%	32	30%	36	34%

Frequency distributions—social value (n = 107)

Statement	Strongly Disagree		Disagree		Neutral		Agree		Strongly Agree	
	n	%	*n*	%	*n*	%	*n*	%	*n*	%
SV_1: I like using my smartwatch for sharing my activity progress with others.	23	21%	31	29%	26	24%	18	17%	9	8%
SV_2: Sharing my progress with others helps to keep me motivated.	21	20%	33	31%	25	23%	17	16%	11	10%
SV_3: Using this smartwatch supports my lifestyle.	6	6%	5	5%	21	20%	56	52%	19	18%

Appendix B. ANOVA Results

ANOVA—SQB by smartwatch brand

Source of Variation	*SS*	*df*	*MS*	*F*	*p*	Significant
Between Groups	3.67	4	0.92	0.88	0.477	No
Within Groups	106.03	102	1.04			
Total	109.70	106				

ANOVA—PU by SQB

Source of Variation	*SS*	*df*	*MS*	*F*	*p*	Significant
Between Groups	19.80	2	9.90	35.42	<0.0005	Yes
Within Groups	29.06	104	0.28			
Total	48.86	106				

ANOVA—Pleasure by SQB

Source of Variation	*SS*	*df*	*MS*	*F*	*p*	Significant
Between Groups	16.11	2	8.05	17.69	<0.0005	Yes
Within Groups	47.36	104	0.46			
Total	63.47	106				

ANOVA—GPM by SQB

Source of Variation	*SS*	*df*	*MS*	*F*	*p*	Significant
Between Groups	24.53	2	12.26	14.47	<0.0005	Yes
Within Groups	88.15	104	0.85			
Total	112.68	106				

ANOVA—Social value by SQB

Source of Variation	*SS*	*df*	*MS*	*F*	*p*	Significant
Between Groups	22.01	2	11.01	14.11	<0.0005	Yes
Within Groups	81.14	104	0.78			
Total	103.15	106				

References

1. Guk, K.; Han, G.; Lim, J.; Jeong, K.; Kang, T.; Lim, E.-K.; Jung, J. Evolution of wearable devices with real-time. *Nanomaterials* **2019**, *9*, 813. [CrossRef] [PubMed]
2. Jovanov, E. Wearables meet IoT: Synergistic personal area networks (SPANs). *Sensors* **2019**, *19*, 4295. [CrossRef] [PubMed]
3. Hosseini, M.M.; Hosseini, S.T.M.; Qayumi, K.; Hosseinzadeh, S.; Sajadi Tabar, S.S. Smartwatches in healthcare medicine: Assistance and monitoring; a scoping review. *BMC Med. Inform. Decis. Mak.* **2023**, *23*, 248. [CrossRef] [PubMed]
4. Köhler, C.; Bartschke, A.; Fürstenau, D.; Schaaf, T.; Salgado-Baez, E. The value of smartwatches in the health care sector for monitoring, nudging, and predicting: Viewpoint on 25 years of research. *J. Med. Internet Res.* **2024**, *26*, e58936. [CrossRef] [PubMed]
5. Parthipan, V.; Ramesh, P.S.; Gururama Senthilvel, P.; Dineshkumar, R.; Vennila, G. Revolutionizing healthcare with wearable devices and IoT integration for personalized health management in next-generation health informatics. In Proceedings of the 2024 International Conference on Recent Advances in Science and Engineering Technology (ICRASET), Mandya, India, 21–22 November 2024.
6. Asimakopoulos, S.; Asimakopoulos, G.; Spillers, F. Motivation and user engagement in fitness tracking: Heuristics for mobile healthcare wearables. *Informatics* **2017**, *4*, 5. [CrossRef]
7. Chuah, S.H.-W. You inspire me and make my life better: Investigating a multiple sequential mediation model of smartwatch continuance intention. *Telemat. Inform.* **2019**, *43*, 101245. [CrossRef]
8. Lu, Y.; Zhou, Z.; Li, X. Study on the relationship between technology, data and body isomorphism—The example of smartwatches. *Telemat. Inform. Rep.* **2024**, *13*, 100118. [CrossRef]
9. Da Silva, J.F.; Germano-Soares, A.H.; Silva, L.C.B.; Barbosa Filho, V.; de Oliveira, T.V.; Silva, T.; Tassitano, R.M. Smartwatches and measurement of physical activity, sedentary behavior, and sleep: A scoping review. *Rev. Bras. Ativ. Fís. Saúde* **2025**, *29*, e0367. [CrossRef]
10. Cho, W.-C.; Lee, K.Y.; Yang, S.-B. What makes you feel attached to smartwatches? The stimulus–organism–response (S–O–R) perspectives. *Inf. Technol. People* **2019**, *32*, 319–343. [CrossRef]
11. Takiddeen, N.; Zualkernan, I. Smartwatches as IoT edge devices: A framework and survey. In Proceedings of the Fourth International Conference on Fog and Mobile Edge Computing (FMEC), Rome, Italy, 10–13 June 2019. [CrossRef]
12. Peng, C.; Xi, N.; Zhao, H.; Hamari, J. Acceptance of wearable technology: A meta-analysis. In Proceedings of the 55th Hawaii International Conference on System Sciences, Maui, HI, USA, 4–7 January 2022.
13. Ha, T.; Beijnon, B.; Kim, J.-H. Examining user perceptions of smartwatch through dynamic topic modeling. *Telemat. Inform.* **2017**, *34*, 1262–1273. [CrossRef]
14. Stiglbauer, B.; Weber, S.; Batinic, B. Does your health really benefit from using a self-tracking device? Evidence from a longitudinal randomized control trial. *Comput. Hum. Behav.* **2019**, *94*, 131–139. [CrossRef]
15. El-Amrawy, F.; Nounou, M.I. Are currently available wearable devices for activity tracking and heart rate monitoring accurate, precise, and medically beneficial? *Healthc. Inform. Res.* **2015**, *21*, 315–320. [CrossRef] [PubMed]
16. Bai, Y.; Tompkins, C.; Gell, N.; Dione, D.; Zhang, T.; Byun, W. Comprehensive comparison of Apple Watch and Fitbit monitors in a free-living setting. *PLoS ONE* **2021**, *16*, e0251975. [CrossRef] [PubMed]
17. Maltseva, K.; Lutz, C. A quantum of self: A study of self-quantification and self-disclosure. *Comput. Hum. Behav.* **2018**, *81*, 102–114. [CrossRef]
18. Siepmann, C.; Kowalczuk, P. Understanding continued smartwatch usage: The role of emotional factors. *Electron. Mark.* **2021**, *31*, 795–809. [CrossRef]
19. Kang, H.; Jung, E.H. The smart wearables-privacy paradox: A cluster analysis of smartwatch users. *Behav. Inf. Technol.* **2020**, *40*, 1755–1768. [CrossRef]
20. Dhar, R.; Wertenbroch, K. Consumer choice between hedonic and utilitarian goods. *J. Mark. Res.* **2000**, *37*, 60–71. [CrossRef]
21. Kamal Basha, N.K.; Aw, E.C.-X.; Chuah, S.H.-W. Are we so over smartwatches? Or can technology, fashion, and psychographic attributes sustain smartwatch usage? *Technol. Soc.* **2022**, *69*, 101952. [CrossRef]
22. Huh, K.T.; Lee, Y.; Kim, S.-H. Self-quantification of services: Cost of real-time feedback. *J. Bus. Res.* **2023**, *164*, 113947. [CrossRef]
23. Zhang, Y.-D.; Zhang, H.-L.; Xie, J.-Q.; Zhang, C.-B. The influence of self-quantification on individual's participation performance and behavioral decision-making in physical fitness activities. *Humanit. Soc. Sci. Commun.* **2023**, *10*, 592. [CrossRef]
24. Etkin, J. The hidden cost of personal quantification. *J. Consum. Res.* **2016**, *42*, 967–984. [CrossRef]
25. Warburton, D.E.; Charlesworth, S.; Ivey, A.; Nettlefold, L.; Bredin, S.S. A systematic review of the evidence for Canada's physical activity guidelines for adults. *Int. J. Behav. Nutr. Phys. Act.* **2010**, *7*, 39. [CrossRef] [PubMed]
26. World Health Organization. A Healthy Lifestyle—WHO Recommendations. Available online: https://www.who.int/europe/news-room/fact-sheets/item/a-healthy-lifestyle---who-recommendations (accessed on 6 February 2026).
27. Dempsey, P.C.; Thyfault, J.P. Physiological responses to sedentary behaviour. In *Sedentary Behaviour Epidemiology*; Springer: Cham, Switzerland, 2018; pp. 109–153.

28. World Health Organization. Physical Activity. Available online: https://www.who.int/health-topics/physical-activity (accessed on 6 February 2026).
29. Meyer, A.N.; Murphy, G.C.; Zimmermann, T.; Fritz, T. Enabling good work habits in software developers through reflective goal-setting. *IEEE Trans. Softw. Eng.* **2021**, *47*, 1872–1885. [CrossRef]
30. Phaswana, M.; Gordon, N.F.; Gradidge, P.J.-L. Sedentary behavior, physical activity patterns, and cardiometabolic risk factors in South African office-based workers. *Am. J. Lifestyle Med.* **2023**, 15598276231210479.
31. Degroote, L.; De Bourdeaudhuij, I.; Verloigne, M.; Poppe, L.; Crombez, G. The accuracy of smart devices for measuring physical activity in daily life: Validation study. *JMIR mHealth uHealth* **2018**, *6*, e10972. [CrossRef] [PubMed]
32. DAMA International. *DAMA-DMBOK: Data Management Body of Knowledge*, 2nd ed.; Technics Publications: Basking Ridge, NJ, USA, 2017.
33. Rapp, A.; Cena, F. Personal informatics for everyday life: How users without prior self-tracking experience engage with personal data. *Int. J. Hum.-Comput. Stud.* **2016**, *94*, 1–17. [CrossRef]
34. Li, I.; Dey, A.; Forlizzi, J. A stage-based model of personal informatics systems. In Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Atlanta, GA, USA, 10–15 April 2010.
35. Dooley, E.E.; Golaszewski, N.M.; Bartholomew, J.B. Estimating accuracy at exercise intensities: A comparative study of self-monitoring heart rate and physical activity wearable devices. *JMIR mHealth uHealth* **2017**, *5*, e7043. [CrossRef] [PubMed]
36. Ricchio, K.; Lyter-Antonneau, P.; Palao, J.M. Reliability of fitness trackers at different prices for measuring steps and heart rate: A pilot study. *Cent. Eur. J. Sport Sci. Med.* **2018**, *24*, 57–64. [CrossRef]
37. Nelson, M.B.; Kaminsky, L.A.; Dickin, D.C.; Montoye, A.H.K. Validity of consumer-based physical activity monitors for specific activity types. *Med. Sci. Sports Exerc.* **2016**, *48*, 1619–1628. [CrossRef] [PubMed]
38. De Arriba-Pérez, F.; Caeiro-Rodríguez, M.; Santos-Gago, J.M. Collection and processing of data from wrist wearable devices in heterogeneous and multiple-user scenarios. *Sensors* **2016**, *16*, 1538. [CrossRef] [PubMed]
39. Boukhechba, M.; Barnes, L. SWear: Sensing using WEARables—Generalized human crowdsensing on smartwatches. In Proceedings of the 11th International Conference on Applied Human Factors and Ergonomics, San Diego, CA, USA, 16–20 July 2020.
40. Buelga Suárez, M.; Rebolleda Sánchez, A.; Pascual Izco, M.; García Montalvo, J.; Alonso Salinas, G.L. Smartwatch: Looking beyond what you see. *J. Electrocardiol.* **2023**, *81*, 51–59. [CrossRef] [PubMed]
41. Bölen, M.C. Exploring the determinants of users' continuance intention in smartwatches. *Technol. Soc.* **2020**, *60*, 101209. [CrossRef]
42. Salim, F.; Kim, S. "I can feel what I used": A diary study of smartwatch features and emotional experiences. In Proceedings of the MobileHCI '23 Companion, Athens, Greece, 26–29 September 2023.
43. Blascheck, T.; Besançon, L.; Bezerianos, A.; Lee, B.; Isenberg, P. Glanceable visualization: Studies of data comparison performance on smartwatches. *IEEE Trans. Vis. Comput. Graph.* **2019**, *25*, 630–640. [CrossRef] [PubMed]
44. Epstein, D.A. Everyday Personal Informatics. Doctoral Dissertation, University of Washington, Seattle, WA, USA, 2018.
45. Almalki, M.; Gray, K.; Sanchez, F.M. The use of self-quantification systems for personal health information: Big data management activities and prospects. *Health Inf. Sci. Syst.* **2015**, *3*, S1. [CrossRef] [PubMed]
46. Luo, Y.; Yang, L.; Ye, Q.; Liao, Q. Effects of customization and personalization affordances on perceived value and continuance intention of smartwatch use. *Technol. Forecast. Soc. Change* **2023**, *194*, 122752. [CrossRef]
47. Yang, J.; Jong, D. Understanding continuance intention determinants to adopt online health care community: An empirical study of food safety. *Int. J. Environ. Res. Public Health* **2021**, *18*, 6514. [CrossRef] [PubMed]
48. Lin, F.-R.; Windasari, N.A. Continued use of wearables for wellbeing with a cultural probe. *Serv. Ind. J.* **2019**, *39*, 1140–1166. [CrossRef]
49. Pfeiffer, J.; von Entress-Fürsteneck, M.; Urbach, N.; Buchwald, A. Quantify-me: Consumer acceptance of wearable self-tracking devices. In Proceedings of the European Conference on Information Systems (ECIS), Istanbul, Turkey, 12–15 June 2016.
50. Findeis, C.; Salfeld, B.; Voigt, S.; Gerisch, B.; King, V.; Ostern, A.R.; Rosa, H. Quantifying self-quantification: A statistical study on individual characteristics and motivations for digital self-tracking in young- and middle-aged adults in Germany. *New Media Soc.* **2023**, *25*, 2300–2320. [CrossRef]
51. George, J.; Bhila, T. The role of mobile health application on self-quantification. *J. Pure Appl. Sci.* **2019**, *1*, 6–15. [CrossRef]
52. Oliver, R.L. Cognitive, affective, and attribute bases of the satisfaction response. *J. Consum. Res.* **1993**, *20*, 418–430. [CrossRef] [PubMed]
53. Oppermann, L.E. Personal Quantification—The Impact of Self-Quantification and Social Sharing on Customers. Master's Thesis, University of Innsbruck, Innsbruck, Austria, 2022.
54. Pennington, N.; Dam, L. Social interaction, support preferences, and wearable health trackers. *Front. Commun.* **2023**, *8*, 1256452. [CrossRef]
55. Saunders, M.N.; Lewis, P.; Thornhill, A. *Research Methods for Business Students*, 8th ed.; Pearson: Harlow, UK, 2020.
56. Jones, T.; Baxter, M.; Khanduja, V. A quick guide to survey research. *Ann. R. Coll. Surg. Engl.* **2013**, *95*, 5–7. [CrossRef] [PubMed]

57. Landais, L.L.; Jelsma, J.G.; Dotinga, I.R.; Timmermans, D.R.; Verhagen, E.A.; Damman, O.C. Office workers' perspectives on physical activity and sedentary behaviour: A qualitative study. *BMC Public Health* **2022**, *22*, 621. [CrossRef] [PubMed]
58. Jenkins, K.; Buchan, J.; Rhodes, R.E.; Hamilton, K. Workplace movement: A qualitative study on office workers' beliefs. *Aust. J. Psychol.* **2024**, *76*, 2341695. [CrossRef] [PubMed]
59. Makkonen, M.; Silvennoinen, M.; Nousiainen, T. To sit or to stand, that is the question. *Int. J. Netw. Virtual Organ.* **2017**, *17*, 371–391. [CrossRef]
60. Babbie, E.R. *The Basics of Social Research*, 7th ed.; Cengage Learning: Boston, MA, USA, 2017.
61. Laricchia, F. Smartwatch Market Share Worldwide from 2020 to 2022. Available online: https://www.statista.com/statistics/1296818/smartwatch-market-share/ (accessed on 14 March 2026).
62. Kline, R.B. *Principles and Practice of Structural Equation Modeling*, 4th ed.; The Guilford Press: New York, NY, USA, 2016.
63. DeVellis, R.F. *Scale Development: Theory and Applications*, 4th ed.; Sage: Thousand Oaks, CA, USA, 2017.
64. Hair, J.F.; Black, W.C.; Babin, B.J.; Anderson, R.E. *Multivariate Data Analysis*, 8th ed.; Cengage: Boston, MA, USA, 2019.
65. Hong, J.-C.; Lin, P.-H.; Hsieh, P.-C. The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch. *Comput. Hum. Behav.* **2017**, *67*, 264–272. [CrossRef]
66. Wang, N.; Xie, W.; Ali, A.; Brem, A.; Wang, S. How do individual characteristics and social capital shape users' continuance intentions of smart wearable products? *Technol. Soc.* **2022**, *68*, 101818. [CrossRef]
67. Suyidno, S.; Nur, M.; Yuanita, L.; Prahani, B.K. Validity of creative responsibility based learning. *IOSR J. Res. Method Educ.* **2017**, *7*, 56–61. [CrossRef]
68. Gravetter, F.J.; Wallnau, L.B. *Statistics for the Behavioral Sciences*, 10th ed.; Cengage Learning: Boston, MA, USA, 2015.
69. Sullivan, G.M.; Artino, A.R.J. Analyzing and interpreting data from Likert-type scales. *J. Grad. Med. Educ.* **2013**, *5*, 541–542. [CrossRef] [PubMed]
70. Kim, D. Analysis of the physical activity enhancement attributes of smartwatches. *Res. Danc. Phys. Act.* **2024**, *8*, 9–23. [CrossRef]
71. Bekker, C.; Scholtz, B. An evaluation of health data accessibility and sharing features of smartwatches used by South Africans. In Proceedings of the 2024 IST-Africa Conference (IST-Africa), Dublin, Ireland, 20–24 May 2024.
72. Lewis-Beck, M.S.; Bryman, A.; Futing Liao, T. Threshold effect. In *The SAGE Encyclopedia of Social Science Research Methods*; Sage: Thousand Oaks, CA, USA, 2004.
73. Jung, E.H.; Kang, H. Self-determination in wearable fitness technology. *Int. J. Hum.-Comput. Interact.* **2022**, *38*, 1399–1409. [CrossRef]
74. Beh, P.K.; Ganesan, Y.; Iranmanesh, M.; Foroughi, B. UTAUT2 smartwatch adoption model. *Behav. Inf. Technol.* **2019**, *40*, 282–299. [CrossRef]

Disclaimer/Publisher's Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.