A Comprehensive Framework of Usability Issues Related to the Wearable Devices

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1 Introduction

Continual innovation in hardware and software technologies, such as sensors, displays, processors, storage memory, and algorithms, has been crucial in changing the paradigm of computing devices. Mobile computing has advanced rapidly over the past decade, and the components found in such computing devices are becoming increasingly smaller while remaining extremely powerful. The emergence of quantified-self technologies, including wearable devices, is one of the most evident examples of this technological development.

Wearable devices can be defined as, "smart electronic devices available in various forms; located near or on the human body to sense and analyze physiological and psychological data such as feelings, movements, heart rate, blood pressure, and so forth, via applications either installed on the device itself or on an external device (i.e., smartphones that are connected to the cloud)" (p.2) [1]. According to Motti and Caine [2], "since the first sensors were produced, the wearable device field has evolved exponentially" and "is characterized by body-worn devices, such as clothing and accessories" (p.1820). Humans use wearable devices in their daily

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activities to gather and assess a diverse range of data “from internal states (as mood or glucose level in the blood) to performance values (as pace or kilometers run), from habits (as food, sleep) to actions (as visited places)” (p.1) [3]. Lee et al. [4] note that in many applications areas (“i.e. areas of wellness, healthcare, assistance for the visually impaired, disaster relief, and public safety” (p.15), the development of wearable devices has contributed significantly to enhancing the quality of daily life of both individuals and society as a whole. It is expected that in the upcoming year, virtual reality (VR) headsets, such as Samsung VR, will be used as an alternative to conventional televisions, and Microsoft HoloLens and similar devices will enhance human vision. In addition, it is anticipated that smartwatches and mobile devices will assist users with health monitoring, for example, by making it possible for patients to monitor a bacterial infection or their glucose levels. In particular, wearable devices are more and more being seen as integral to a future in which users will control devices remotely via the Internet.

Despite the potential benefits of wearable device usage, numerous researchers have generally recognized that wearable technologies are failing to inspire long-term adoption [5–7]. For example, Lazar et al. [6] find that their participants abandoned almost 80% of their purchased wearable devices within the first 2 months because of deficiencies in usability. Another study by Endeavor Partners [7] reports that many wearable device users abandoned their devices within 6 months of initial usage because of poor experiences. Clawson et al. [5] indicate that individuals abandoned their wearable devices because (i) they were too complicated to use; (ii) they were too complex to learn; or (iii) they failed to help the users achieve their goals. Although the principal objective of these wearable devices is to provide the user with higher levels of ease and flexibility [8] in data acquisition without any degree of intrusiveness [9], usability is seen as one of the more influential factors associated with device abundancy. Furthermore, Piwek et al. [10] state that “wearable devices don’t add functional value that is already expected from personal technology of that type, and they require too much effort, which breaks the seamless user experience” (p.3). Moreover, Motti and Caine [2] assert that “by focusing on the feasibility of an individual approach, often usability and wearability are neglected” (p.1821) on wearable devices. As asserted by Abbas [11], “The outcome of good usability is a greater likelihood of user acceptance. User acceptance is often the difference between a product’s success or failure in the marketplace” (p.1764). Trivedi [12] also states, “The user is concentrating on the usability of the device. Therefore, usability has become an important parameter today” (p.69).

The term “usability” is derived from ISO standard 9241-11, where usability is described as the “extent to which a product can be used by specified users to achieve specified goals with effectiveness, efficiency and satisfaction in a specified context of use” [13]. Usability can also be construed as the value that users derive from using the technology or device. Gafni [14] states, “Usability is one of the most important characteristics when targeting systems to wide audiences that need to operate an intuitive system without direct training and support” (p.755). However, inappropriate design, lack of context-awareness will affect the usability while interacting with devices and interrupt individual to accomplish their goals [15, 16].

Therefore, usability parameters are extremely important to the success of wearable devices because they enable users to derive the full benefits of the device without requiring specific training or additional guidance [11, 12, 16, 17].

We argue that to improve the usability of wearable devices and increase their long-term use, it is first necessary to identify and then understand usability-related issues, especially regarding in which wearable device categories previous research has addressed these issues. Thus, the current study undertakes a systematic literature review (SLR) that follows the method presented by Petersen et al. [18]. An SLR presents an opportunity to closely review the current state-of-the-art [19] by synthesizing evidence to signify critical implications [20], identify unresolved problems, discover research trends, and create a basis for novel intervention.

The present work seeks to identify, understand, evaluate, and synthesize usability issues in the wearable device's domain including which usability evaluation methodology has been applied by the researchers. The time span considered begins in 2000, when based on Google trends and Motti and Caine [2] report, wearable devices were first introduced and marketed,[1] and ends in January 2018.

The rest of the paper is organized as follows: Sect. 2 presents a brief synopsis of the motivation and related work; Sect. 3 discusses how the research process was carried out to provide definitive results for the research questions (RQs); Sect. 4 presents the findings and interprets the results; Sect. 5 discusses the significance of the results and presents the limitations of the study; and Sect. 6 concludes the work by restating the main points made in the study and indicating future areas of study.

2 Related Work

As the field of mobile technology has advanced, wearable sensors that collect data from human activity have emerged [21]. Because these wearable devices are completely different from mobile devices in terms of their size, functionality, user interaction, and platform, their integration into people's daily lives poses a variety of challenges [22]. Finding the right balance between attributes such as "accessibility, usability, and wearability" [23] in wearable device remains difficult. One of the difficulties stems from the unique interaction modalities of these devices compared with other computing devices, especially in terms of the input-output mechanisms, which require a new design approach [2]. Because wearable devices are a comparatively new field of study, there are inadequate number of studies that have reviewed and analyzed usability and its relation to different types of wearable devices. For example, Motti and Caine [2] literature review identifies wearability principles. The study considers device characteristics, that is, hardware and software, arguing that 20 human-centered principles could help designers

[1]The history of wearable technology – Past, present and future. https://wtvox.com/featured-news/history-of-wearable-technology-2/

understand the design process and facilitate design with the focus on "users' wishes, interests, and requirements." The study concludes that even though these principles could overcome some obstacles, helping designers focus more on design than human factors when developing novel wearables, trade-offs such as technical and ergonomics requirements still require careful analysis. Similarly, Dhawale and Wellington [24] use an ethnographic study to identify the usability characteristics of activity monitoring devices and how these characteristics encourage the prolonged use of such devices. They focus on identifying the usability issues of these particular monitoring devices versus a larger sample with multiple wearable devices. The study identifies six key usability characteristics that play a vital role for device users: "display size of the screen, weight of the device, battery life, multitasking, social engagement, and ease of use." Other authors, for example, Jiang et al. [25] reviewed how and why wearable devices are developed and why they have gained popularity in recent years. Their work includes a consideration of the classification standards of wearable devices, focusing mainly on software-related device characteristics issues. The study concludes that even though wearable devices have gained momentum in recent years, they are still at an immature stage of development. The authors claim, "Hardware materials and battery life still has not had a breakthrough: limited screen space makes the product design difficult, and application software is still in an initial stage" (p.597).

One observation from these studies is that wearable devices are available in various form factors (size, shape, style, etc.) and that these various form factors and the environments the wearables are used within can affect usability, which in turn impacts on the user acceptance and engagement. Another observation from prior research suggests that previous studies have examined wearable devices and identified usability issues such as screen size, battery life, connection, software and are scattered across the literature, and there are relatively no studies that focus on review and analyze usability and its relation to which types of wearable devices and thus, a need to fill this research gap. Therefore, this chapter aims to fill this research gap by presenting an in-depth, formal, and inclusive review. To present a holistic overview of studies on usability issues related to wearable devices, the present study builds a categorization scheme to identify various types of usability issues and how they have been identified in previous studies.

3 Methods

Based on the guidelines provided by Kitchenham and Charters [26], Engström and Runeson [27], and Petersen et al. [18], an SLR approach was adopted and applied for the current study; these guidelines describe a streamlined SLR approach that researchers follow to gather the necessary data from a pool of scientific literature and how to evaluate and categorize the data in an unbiased way based on the relevancy of the formulated research problem (Kitchenham and Charters [26]). Steiger et al.

[19] assert that "conducting a systematic literature review is an efficient way to select the best available research and facilitates research approaches by identifying current existing research gaps and study limitations" (p.21).

The main advantage of an SLR approach is that it provides information about the effects of a phenomenon across a wide range of settings and empirical methods with the possibility to combine data using meta-analytic techniques [28]. The adopted process consists of the following phases:

- *Define* the research questions (RQs), based on research goals and objectives.
- *Develop* a review protocol that specifies the search, selection, data extraction, and synthesis strategies [29].
- *Conduct* a scientific literature search to identify the primary literature by using generated search strings on electronic databases that consists of articles from conference proceedings, and journal publications. Search string generation sometimes requires an iterative approach before suitable search terms and values can be found.
- *Screen* the preliminary set of identified literature by utilizing inclusion and exclusion criteria (i.e., find the papers that fulfill the objectives given by the research questions, etc.).
- *Categorize* the selected literature based on the set of keywords which is crucial in identifying relevant primary studies [1].
- *Present* the results in a visual form (i.e., in graphs, tables, or other informative graphical representations).

Petersen et al. [18] recommend that researchers doing SLRs should use alternative ways to present and visualize their results. Following the advice and based on extracted data from the selected articles, the current SLR presents the results in graphs, tables, and figures.

3.1 Research Questions

Tosi and Morasca [29] state that "defining research questions is an essential part of the SLR, as they drive the entire review methodology" (p.19). The current SLR identifies usability-related issues and user interface-related issues in wearable devices, investigating how these issues were discovered. Petticrew and Roberts [30] and Kitchenham et al. [31] both suggest using the population, intervention/issue, comparison, and outcome (PICO) framework to formulate the SLR research question. The PICO framework defines research questions by providing the criteria for defining keywords, structuring the final search string, and formulating the inclusion and exclusion criteria. The overall principles of PICO are applicable to any search strategy; however, some PICO elements can be discarded depending on the nature of the research. In the current study, the aims do not include comparing issues related to wearable devices; instead, the focus is on discovering the pertinent issues. Because a comparison is beyond the scope of the current work, this element was thus omitted. Hence, the following four research questions (RQs) were formulated:

RQ1: To date, what categories of usability issues related to wearable devices have been discussed in the past, and which issues relating to wearables still persist and need further investigation?

Rationale: Defines the basis of the SLR, allows us to identify, evaluate, and categorize the range of usability issues and get an overview of the usability issues through a categorization framework (i.e., the issues that have been presented and discussed, along with their implications). The results that answer RQ1 will enable the researchers, practitioners, and application developers to understand and obtain a more holistic overview on which issues currently exist, what caused those issues to appear in the first place, and which issues are associated with which type of wearable device categories. The sub-question of RQ1 provides detailed information on the challenges that still remain and the improvements required to alleviate them, serving as a basis for future research directions. Previous studies indicate that usability as factor that influences abandonment of the devices of the wearable devices; this paper identifies and presents a categorization framework that allows researchers, practitioners, and application developers to understand and obtain a more holistic overview on which usability issues are associated with which type of wearable device categories that act as the barriers to user adoption, facilitating the adoption of wearable device.

RQ2: How have usability evaluation methods (UEMs) been applied to wearable device evaluation and in which device categories?

Rationale: Identifies the range of the most commonly used UEMs and their subsets to obtain an overview on which UEMs have been employed to evaluate the categories of wearable devices. The result obtained from RQ2 will enable researchers, practitioners, and application developers to understand and make decisions while selecting the UEM for a particular type of device evaluation.

3.2 Search Design and Process

The primary studies used in the current paper were identified using search strings on scientific digital databases. In addition, a manual search was done through relevant conference proceedings and journal publications, which is explained in detail below. The automated search process was conducted on the following digital databases: “IEEE Digital Library,” “ACM Digital Library,” “Springer Link,” “Science Direct,” and “others: Google Scholar,” These databases were selected because they are the preeminent sources of published research in the engineering field. The aim was to find as many notable publications that discuss usability issues related to wearable

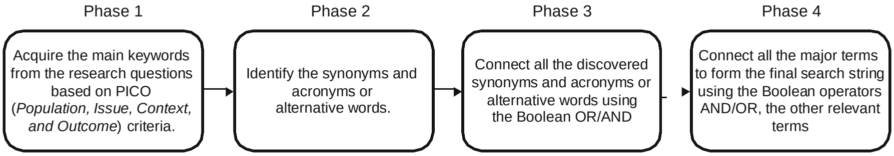

Fig. 1 Search string formulation process

devices as possible. Figure 1 shows the four phases of search string formulation process presented by [1].

In Phase 1, the main keywords relating to the research questions (see Sect. 3.1) were acquired using Population, Intervention, Comparison, and Outcome (PICO) criteria[2] (i.e., “wearable device” and (“usability issue”). Kitchenham et al. [31] recommend the use of keywords from the comparison and outcome criteria when formulating the search string; this was not carried out in the current work because it is only a common procedure in the field of medical science. Kitchenham et al. [31] and Petersen et al. [18] also note that using keywords from the comparison and outcome criteria is not always applicable. In the present case, the use of a comparison was discarded when the research questions were formulated, and the outcome was not taken into account because the current study does not aim to measure effects. In Phase 2, the identification of synonyms and acronyms or alternative words took place. One of the constraints when formulating a search string is that the resulting set should have the maximum possible coverage but should remain at a manageable size. Therefore, several synonyms (“wearable devices,” “wearable computing,” and “wearable technology*”) were used. In Phase 3, Boolean “OR” was applied to merge all the discovered synonyms and acronyms or alternative words [1]. Lastly, in Phase 4, Boolean operator “AND” was applied to connect all the keywords and to formulate the final search string for relevant articles published after the year 2000 as (“wearable*” or “wearable device*” or “wearable computing” or “wearable technology*”) AND (““usability issue*” or “usability”) AND (“publication year>2000”).

In January 2018, an initial search was conducted utilizing the formulated search string and the search utility of the selected digital databases. The final set of searches was performed in February 2018. Additional search was also performed using online web search engine “Google Scholar” to find if any further relevant articles exist and “cross-check the final sets of retrieved papers to determine the relevance of each paper” [2].

[2]PICO Criteria: http://learntech.physiol.ox.ac.uk/cochrane_tutorial/cochlibd0e84.php

3.3 Article Selection Process

The article selection process in the current study is defined as a process of extracting the relevant publications with respect to the objective of the SLR based on inclusion criteria (IC) and exclusion criteria (EC). Hence, in this context, the subsequent set of IC and EC were formulated and applied to select the relevant publications:

- *IC1:* Publication is dated between 1/1/2000 and 02/2018.
- *IC2:* It comprises answers to at least one of the presented research questions, which was determined by reading the title and abstracts.
- *IC3:* Publication is written in English.
- *IC4:* If various similar papers are outlined by the same author, only the most current publication is used.
- *EC1:* Publication lies outside the wearable devices domain.
- *EC2:* The publication does not cover the usability-related topic within the domains of wearable devices.
- *EC3:* Technical documentation or reports.

Based on the above ICs and ECs, the article selection process was conducted in four individual phases, as shown in Fig. 2. During Phase 1, an automated search was performed using search strings to identify potential studies. This preliminary search yielded 3271 papers.

In Phase 2, the articles (title, keywords, and abstract) obtained in Phase 1 were reviewed, and the ICs and ECs were applied to select the articles for the next phase of the process. As a result, 350 articles were selected, and 3271 articles were excluded. In Phase 3, a review of the full text of the selected original articles from the previous phase was conducted to determine the articles' relevance and whether the articles should be included for further analysis. Finally, 84 articles were considered suitable, while 266 were excluded because they were not relevant to the RQs, had too little in the way of content, or were not in English (i.e., the abstract, keywords, and title were in English, but the body of the article was in another language). Thus, 84 articles were identified as relevant primary studies for data extraction. Of the 84 studies reviewed, 34 were published in the ACM digital library and rest on the other electronic databases (i.e., Springer, Science Direct, IEEE, BioMed Central, Hindawi, Taylor and Francis, Journal of Medical Internet Research, and Journal of Computer-Mediated Communication), respectively.

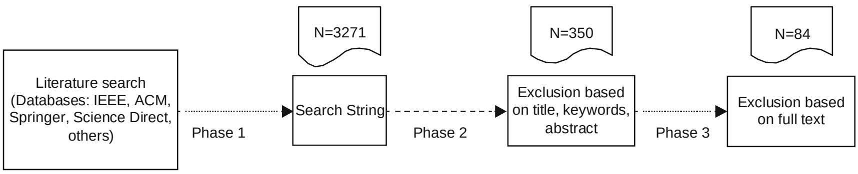

Fig. 2 Article selection process for choosing relevant primary studies

3.4 Data Extraction and Synthesis

Because the results presented in the current paper are based on the qualitative assessment of the previous literature, the process of data extraction and synthesis is described below. According to Welsh [32], in a qualitative data analysis, to avoid human errors and when organizing the data, "it is important that researchers do not reify either electronic or manual methods and instead combine the best features of each" (p.5). Following this recommendation, both computer-based and manual analysis techniques were applied. Furthermore, the approach applied for the data extraction and synthesis process consisted of six phases.

In the first phase, all the relevant articles were exported to the NVivo data analysis tool (version 11) [33] for data analysis from the Mendeley reference management tool [34]. NVivo data analysis tool was applied because it allows for sophisticated data coding and helps map out diagrammatically how the themes relate to each other [32, 35]. After the final set of relevant articles were transferred to NVivo, the initial nodes were created on NVivo based on the main themes: usability issues; usability evaluation method; target group; wearable device categories; wearing position; geographical locations; application domain; and age group. Further nodes were created under the usability evaluation method based on the taxonomy of Ivory and Hearst [36], that is, the method class, method type, automation type, and effort level.

In the second phase, each relevant article was read, and important sections of the text were coded. During the coding process, either phrases, paragraphs, or single words were highlighted and added with links to the initial nodes (i.e., themes) from Phase 1. For example, text from one study that was coded and added within the "usability issues" node could be as follows: "all of them experienced automatic loss of synchronization, making it difficult or impossible to update data or resulting in an incorrect report" [37] (p.8).

To improve accuracy, printed copies of articles were read, and themes were highlighted. Coded data from the NVivo and the highlighted data from the printed copied were compared to see if patterns remained the same on the computer-based and manual method. Some data were missing when analyzed with NVivo. Those data that were missing were added to NVivo. Following this, a node list was generated for debriefing to other researchers. According to Impellizzeri and Bizzini [38], "Data extraction must be accurate and unbiased and therefore, to reduce possible errors, it should be performed by at least two reviewers" (p.499). Based on this recommendation, in the third phase, the initial data sets were reviewed by two members of the research team to confirm that the intended meaning was accurate and appropriate for further analysis. Furthermore, there were no disagreements between the initial datasets.

Because the main goal of the current study is to identify, evaluate, and categorize (i) the usability issues related to wearable devices and (ii) the types of usability evaluation methods that have been discussed in the literature, after the final agreement, in the fourth phase, data related within the node to usability issues and the usability evaluation method were further coded. Nowell et al. [39] note, "Sections of text can be coded in as many different themes as they fit, being uncoded, coded once, or coded as many times as deemed relevant by the researcher" (p.6). For example, for text from one study, "preliminary graphical icons was cumbersome because the icons often … represent" (p.1125) [40] were coded under theme iconography because it described the usability issues related to the icons.

For the manual approach, each text was coded on a printed list of usability issues that were identified in Phase 2, and a theme was given to each identified usability issue. The final sets of data were exported to excel. Data on excel and Nvivo were compared, showing that some themes on Nvivo were missing during the coding of the primary studies. To obtain the agreement among raters and assess intra-rater reliability, we applied Cohen's kappa, in which two raters separately rate the data. The final percent agreement was 0.976, which we can interpret as almost perfect agreement based on Cohen's suggestion that "values ≤ 0 as indicating no agreement and 0.01 – 0.20 as none to slight, 0.21 – 0.40 as fair, 0.41 – 0.60 as moderate, 0.61 – 0.80 as substantial, and 0.81 – 1.00 as almost perfect agreement"(p.6) [41]. A total of 14 data fields were created, which included the following data for each primary source included in the study: study ID (S1, S2, …), title of the paper, citation, year of publication(s), research focus, type of publication, name of the database where the publication was retrieved from. The data that were relevant to what was obtained through the coding process were exported in excel for further analysis and include the following: usability issues (if applicable), wearable device categories (if applicable), wearing position (if applicable), usability evaluation method (UEM) (if applicable), geographical locations (if applicable), application domain (if applicable), and age group. Extracted data were recorded into data fields and are described in more detail online (https://doi.org/10.5281/zenodo.1476457).

4 Results

This section presents the results that were consolidated from the final set of 84 articles (see Appendix A) based on the RQs formulated in Sect. 3.1. The results are presented in the form of graphs, tables with analysis based on the recommendation by Petersen et al. [18]. As shown in Fig. 3, out of 84 articles, 59 were from conferences (70.23%), and the rest were from journals (29.76%). One reason for this may be because the wearable topic has picked up momentum recently, and conferences have a shorter time to publish when compared with an article. However, the increase in the number of publications shows that the field is becoming more important and that people are paying attention to these issues, which is in line with [42], where they claim, "The significant number of papers in conferences and journals is an indicator that the concept has started to get consolidated" (p.51).

Additionally, the study led to the identification of 19 types of wearable devices utilized in the research articles. The identified devices and how they are distributed are shown in Fig. 4. Most of the studies were carried out utilizing smartwatches,

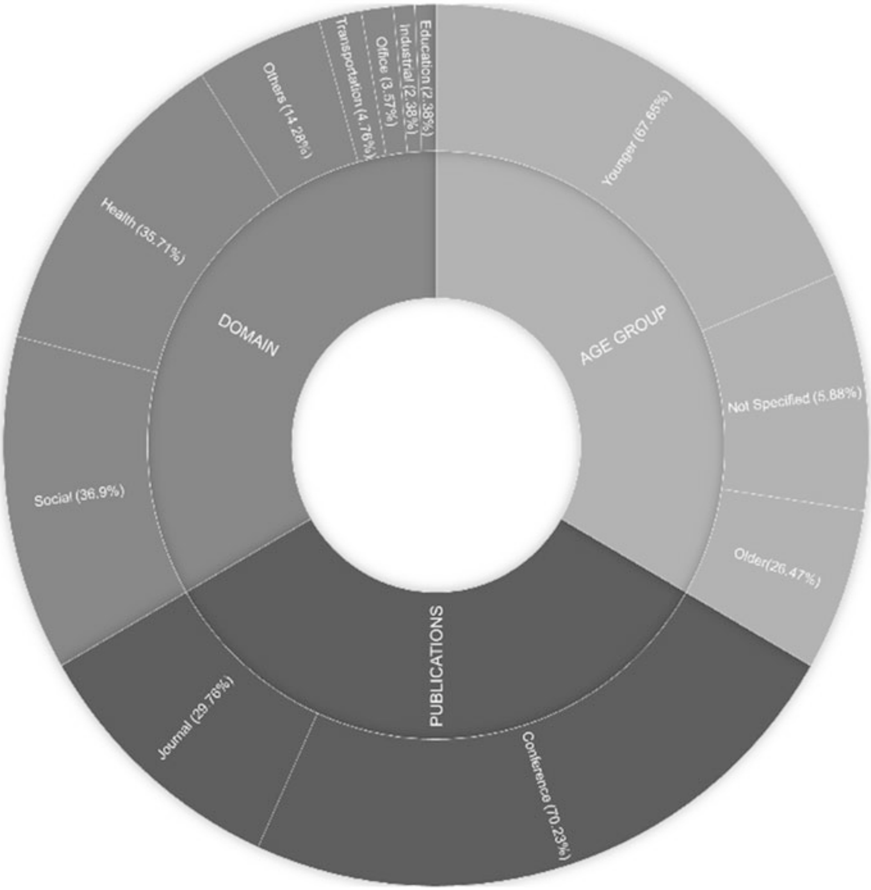

Fig. 3 Descriptive statistics of the publications, age group, and domains of the selected papers

activity tracker/monitor, and wristbands, which are followed by head-mounted displays (HMD) with a binocular configuration (worn over both eyes), either opaque or transparent, for example, virtual reality and smart glasses with AR, and head-mounted displays (HMD) with a monocular configuration (worn over one eye) that is transparent, for example, smart glasses. We speculate that using both commercially off-the-shelf and prototype devices in the selected studies is the reason for having numerous types of wearable device categories.

Additionally, as displayed in Appendix, these identified devices are worn on the wrist (44/84), head (20/84), chest (4/84), finger (3/84), knee (1/84), and the remaining on other parts of the body, such as arms, neck, waist, or feet. The current trend of wearables is mostly wrist-worn and head-worn; however, other body-worn devices are gaining momentum.

In the following section, we discuss how each research question was answered.

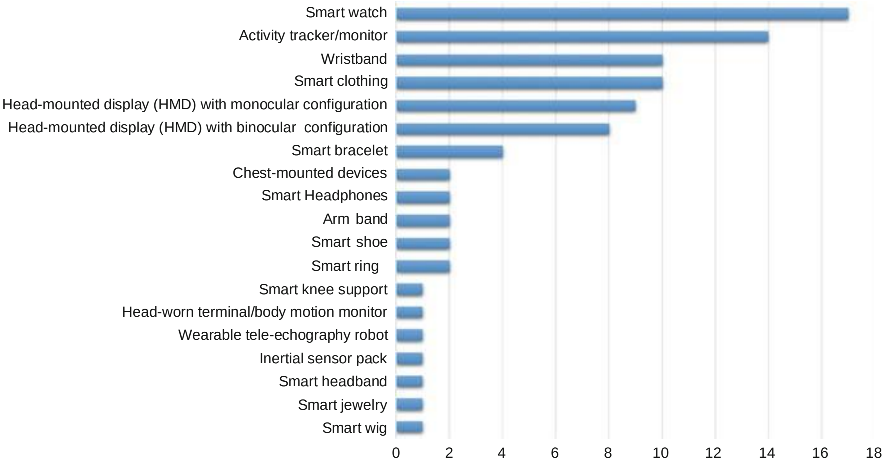

Fig. 4 Categories of wearable technology used in the study

4.1 RQ1: To Date, What Categories of Usability Issues Related to Wearable Devices Have Been Discussed in the Past, and Which Issues Relating to Wearables Still Persist and Need Further Investigation?

The overall aim of this research question was to identify, evaluate, and categorize the set of usability issues related to wearable technologies that have been discussed prior to 2018. The analysis of the primary studies prompted the identification of 20 different types of usability issues related to wearable devices. An example of each in relation to the type of wearable device category is shown in Table 1. As shown in Table 1, most of the identified usability issues are related to smartwatches (15/20), wristbands (12/20), activity trackers/monitors (18/20), head-mounted displays (HMD) with a binocular (worn over both eyes), either opaque or transparent (15/20), and head-mounted displays (HMD) with a monocular (worn over one eye eyes), transparent (14/20). Therefore, we believe the issues related to the devices need immediate attention because these are the most available devices on the market. Similarly, Table 1 also shows that out of the 20 usability issues, screen size, aesthetics (physical design, material, and color), interaction techniques (auditory, visual, gesture, and haptic feedback), wearing position, and motion artifacts were the most reported.

Based on [16, 43], the identified issues in Table 1 were further condensed into device characteristics (see Sect. 4.1.1) and the deployment of wearable devices on the body and external devices (see Sect. 4.1.2).

Table 1 Identified issues in relation to the type of wearable device category

Wearable device categories	Types of associated usability issues																			
	Screen size	Screen display	Lack of screen	Color contrast	Interaction techniques s (auditory, visual, gesture, and haptic feedback)	Button location	Device context	Navigation	Iconography	Elements (fonts/color)	Interaction with the application	Battery	Weight	Memory size	Aesthetics (physical design, material, color)	Wearing position	Motion artifacts	Data accuracy	Device connectivity	Applications on external device
Smartwatch	X	X			X	X	X	X	X		X	X		X	X	X	X	X	X	
Smart wig															X	X				
Smart clothing					X		X					X	X		X	X				X
Smart ring															X	X				
Smart jewelry																X				
Smart shoe															X	X				X
Smart bracelet	X				X		X		X		X				X	X				
Wristband				X	X	X	X	X		X	X				X	X	X	X	X	
Arm band												X			X	X				
Smart headband															X		X			

(continued)

Table 1 (continued)

Wearable device categories	Types of associated usability issues																			
	Screen size	Screen display	Lack of screen	Color contrast	Interaction techniques s (auditory, visual, gesture, and haptic feedback)	Button location	Device context	Navigation	Iconography	Elements (fonts/color)	Interaction with the application	Battery	Weight	Memory size	Aesthetics (physical design, material, color)	Wearing position	Motion artifacts	Data accuracy	Device connectivity	Applications on external device
Smart headphones					X															
Inertial sensor pack					X									X			X			
Activity tracker/monitor	X	X	X		X	X	X	X	X	X	X	X	X		X	X	X	X	X	X
Wearable tele-echography robot																x				

Head-worn terminal/body motion monitor		X			X					X					X					
Smart knee support							X								X					X
Chest-mounted devices					X				X											X
Head-mounted display (HMD) with binocular configuration (worn over both eye) opaque or transparent, for example, virtual reality, smart glasses with AR	X	X		X	X	X	X	X			X	X	X	X	X	X	X		X	
Head-mounted display (HMD) with monocular configuration (worn over one eye) transparent, for example, smart glass	X	X		X	X		X				X	X	X		X	X	X	X	X	X

Device Characteristics

Ally and Gardiner [43] specify that smart mobile computing device characteristics can be classified mainly by two components: physical and user interface aspects. Specifically, the physical component concerns product aesthetics that relate to the external look and feel and internal components, such as sensors, processor, memory, power supply, and transceiver [43, 44]. Lee et al. [4] define the user interface as the way in which users interact with devices while managing their interactions with other machines and the people who are connected to the device.

The categorization resulted in 15 issues related to the device characteristics (out of which 20 were related to the user interface and four to the device's physical aspects). We further clustered the user interface issues based on the user interface fundamentals explained by Dennis et al. [45], who state that "the user interface includes three fundamental parts: the output mechanism (the way in which the system provides the user with information), the input mechanism (the way in which the system captures the information), and the navigation mechanism (the way in which the user gives instructions to the system)" (p.314). The input and navigation mechanisms are combined in the current work because both mechanisms relate to receiving the instructions and system capturing from the user. Nine issues regarding the input and navigation mechanisms were found, and five issues related to the output mechanism were discovered. Moreover, two issues were found to be associated with both the Output mechanism, input and navigation mechanism aspects of the device. A summary of mapped usability issues associated with the device characteristics is shown in Table 2.

Each of the usability issues relating to device characteristics (both user interface and physical) are discussed below to clarify how they impacted the use of wearables among individuals.

Screen size: Considering that most, if not all, other computing devices have screens, wearables are an oddity in that many of them do not have screens. Devices with screens play a vital role in providing better user-device interaction and increase user engagement while delivering content such as quantified-self data, online manuals, and training tools with augmenting devices [24, 46]. Dhawale and Wellington [24] find that screen size was significantly important for participants because "it makes the user interaction with the device easier, smoother and more engaging" (p.41). However, to deliver the wearability, portability, and fashionable characteristics required [47], wearables are designed with very limited display size and shape. For example, head-mounted devices are designed with limited display and shape, and the visual field is only a small central region (23 degrees) [48]. Having such a limited display size and shape restricts the input, output, and navigation capabilities of the devices. Wichrowski et al. [49] use head-mounted display (HMD) with monocular (worn over one eye) configuration for example, Google Glass as a wearable device and find that "screen size is too small to convey a fairly substantial amount of information" (p.4). Similarly, Kim [50] find that screen size and shape affects the information quality and inhibits the content-

Table 2 Summary of the mapped usability and user interface issues associated with wearable devices related to device characteristics (table representations)

Usability issues categories	Usability issues subcategories	Fundamental	Associated usability issues
Device characteristics	User interface	Output mechanism	Screen size
			Screen display
			Lack of screen
			Color contrast
			Interaction techniques (visual, auditor, and haptic feedback)
		Input and navigation mechanism	Screen size
			Interaction techniques (gesture, auditory)
			Button location
			Device vontext (text, time, and visualization)
			Navigation
			Iconography
			Elements (text/button)
			Interaction with the application
			Color contrast
	Physical	External look and feel	Aesthetics (physical design, material, color)
			Weight
		Internal component	Battery
			Memory size

relevant thoughts among users. For example, Kim [50] report, "The large screens inhibited participants from generating thoughts about the specific contents of the given information, such that the messages presented on the large screens elicited fewer content-relevant thoughts than the messages presented on the small screens" (p.131). Moreover, having a small screen size not only limits devices to delivering information, but it also reduces the usability while interacting with the devices and the individuals' intended goals while performing certain tasks, such as reading the messages, navigating within the application, and typing messages. For example, Pulli et al. [51] note the issue of display size: "The display size was too small for easy reading" (p.1125). This can increase the number of user errors, affect efficiency, and alter the individual's decision to continue using the device for a longer period of time [24, 52].

Screen display: The screen display is one of the more influential factors that causes usability issues among individual's interactions with the device because of the display's size, position, or shape [49, 53], technology, such as small prismatic crystal [49], or configuration, such as monocular (i.e., worn over one eye) and transparent or binocular (i.e., worn over both eyes) and transparent [54–56]. For example, Delabrida et al. [54] report that the lenses of head-mounted wearables with an opaque binocular display configuration increased the smartphone screen resolution, leading to higher image resolution and a usability issue among participants. Similarly, Laramee and Ware [56] find that wearable devices with a transparent monocular display configuration negatively impacted the task performance, such as reading and viewing against anything other than uniform background. In addition, McGill et al. [57] report that participants found the opaque view quite disruptive while using HMD devices. Kaewkannate and Kim [37] find that for participants, it was difficult to see the text in sunlight using the current wearable displays.

Lack of screen: To explore new possibilities when it comes to making devices lighter, many device manufacturers have physically discarded the screen; only sensors are used to track the users' daily activities, such as sleep and physical activity, and the data are presented through external devices, such as a smartphone or computer. This state-of-the-art technique has the advantage of utilizing a non-visual user interface (UI) in terms of (i) wearability, for example, being light weight; and (ii) in reducing issues with remembering individuals, for example, charging devices [58]; however, the study identifies that having a non-visual interface brings additional usability challenges. For example, Kaewkannate and Kim [37] find that there are issues related to interaction with the devices (i.e., the device does not respond while tapping its surface); needing to use the apps on external devices to view the information; and data inaccuracy because of the synchronization between the external devices and the wearable.

Color contrast: Color contrast assists individuals in viewing and interacting with content; it consists of elements (i.e., color, text, and graphics) in a dark and bright-light environment. However, the current review indicates that (i) poor color contrast between the background of the user interface and the color of the text affect readability [59] and (ii) visual cues with a higher color contrast have less reaction time among participants [60]. For instance, in the study by Holzinger et al. [59], a participant commented: "Dark grey text? On a light grey background, it is very difficult to read" (p.4). Similarly, Costanza et al. [60] find that when visual cues with a bright color contrast were delivered on the eyewear display of the user, the reaction time was quicker than when there were visual clues with a dim contrast. Wichrowski et al. [49] also state, "All personal graphic elements must meet the requirements of usability. For example: too detailed graphic elements or too many colors can interfere with readability and may not be visible on Google Glass. Therefore, it is necessary to create graphics from a limited number of elements and colors" (p.3).

Interaction technique: Jacob [61] state, "An interaction technique is a way of using a physical input/output device to perform a generic task in a human–computer dialogue and represents an abstraction of some common class of interactive tasks, for example, choosing one of several objects shown on a display screen. Research in this area studies the primitive elements of human–computer dialogues, which apply across a wide variety of individual applications" (p.1). Many of the review papers reveal that wearable devices, from smartwatches to the HMDs, provide many different ways of interaction through several in- and output modalities, including auditory [62], visual [63], haptic feedback (i.e., tactile, kinesthetic) [64], and gesture (i.e., touch, head) [65–68], to enhance the user experience.

Although these interaction techniques have bought new opportunities when it comes to improving the user experience within the interaction domain, the current study shows that it also opens up usability challenges. For example, Kaewkannate and Kim [37] find kinesthetic feedback that relates to force feedback sensed from muscles, joints, and nerves when the user receives output from the device, such as vibrations caused irritation among users during evaluation. One of the causes was because of excessive vibration before the device went into sleep mode. In addition, both Lazar et al. [6] and Zhang and Rau [69] report concerns from participants regarding receiving active feedback, that is, notifications from devices while performing a task. For example, participants commented, “I don’t want to receive messages when I am doing the exercise” [69].

Regarding the touch gesture, studies report the reasons why users encountered problems while interacting with the device’s surface. For instance, the studies note that maintaining touch [70] and touch sensitivity on the device [71, 72], which require frequent tapping on the device surface [68], were some challenges users encountered with tapping. In addition, Pulli et al. [51] analyze tap detection, finding that when users selected a too low detection threshold on the device, they suffered slight pain in their finger. Other studies show that there may be additional challenges related to tapping. For instance, Wichrowski et al. [49] find some participants reported swipe gestures caused challenges because of the placement of the device, for example, “for many students it was not natural to use swipe gestures close to the head” (p.9).

In line with the above challenges, studies indicate that poor speech recognition [49, 62, 63] by the device and needing silence for speech input [62] were the main challenges users discovered while conducting auditory interactions. For example, Neto et al. [62] report that users experienced difficulties while interacting with the device when starting the gear face recognition (GFR) system through speech synthesis. Similarly, Lawo et al. [63] find that using voice as the interaction technique was difficult for participants with an accent. Wichrowski et al. [49] also observe that Google Glass sometimes incorrectly interpreted voice commands.

Button location: The button acts as the meditator between the user and wearable devices, in this case being the item responsible for triggering actions. A user can touch the button either to give instructions or navigate the content within the device. The location of the buttons on both the hardware or on the screen of the wearable devices can affect users’ actions and may lead to serious mistakes. Rasche et al. [73] point out, “The activity tracker just had one button to interact with. Participants reported this interaction design to be difficult and annoying. They had problems feeling the button under the silicon tracker display wristband. The navigation of the activity worked by pushing the button. For example, it was necessary to press the button twice to get the actual time, which was reported to be annoying” (p.1414). Ye et al. [74] also “observed participants feeling along the far side of the wrist to find the top edge of the "Select" button or along the near side to find the bottom edge of the 'Home' button" (p.7). Holzinger et al. [59] assess the behavioral intention and user acceptance of a wrist device. They find that the manual alarm button of the device they study "tended to stick, requiring more pressure to activate than was compatible with an elderly person in need of help" (p.4).

Device context (text, time, and visualization): The literature review indicates that issues surrounding the context of the device were influenced by the text, time, graphics, and visualizations during the interactions with wearables. For example, Altenhoff et al. [75] observe that participants had issues using devices when they realized that there was no option to input decimal amounts (e.g., 10.5 ounces of water). Rasche et al. [73] find that participants would substitute their wrist watch if the trackers permanently displayed the time of day. Ananthanarayan et al. [76] observe that participants found circular LED displays were harder to count and calculate. Device with the Knee-shaped visualizations received a mixed response. The non-linear display was found to be complicated and aesthetically unpleasing among participants.

Navigation: The literature review shows that navigation allows users to easily access the information using (i) touch technologies, such as analog resistive and capacitive, through swipe and tap to navigate within the user interface; (ii) a control button on the side to navigate within the user interface; and (iii) capacitive touchpads with or without light-emitting diode (LED) patterns in conjunction with external devices [37, 75, 77, 78]. However, at the same time, small screen sizes, gesture, buttons, or the lack of a screen, and the limits of user usage behavior [79] (i.e., keep their eyes locked on the device while conducting interactions) impact the efficiency and usability, which includes swiping, difficulties locating settings, menus or icons, and unintentional interruptions during interactions. For example, Thorpe et al. [80] find that participants had difficulties "to know when to stop swiping through the menu on wristwatch" (p.300). Altenhoff et al. [75] discover that several of the Jawbone Up participants had trouble locating and understanding the alarm. Furthermore, one participant was confused about the "smart sleep" setting: " … . but is that before or after?" (p.243). Wulf et al. [81] observe that "initiating the speech interaction by pressing the physical button sometimes led to the problem that the participants forgot to push the button and started speaking without the system listening to them … nor could receive the user's command … Moreover, the interaction was sometimes interrupted unintentionally by pressing the activation button again so that the previous conversation and dialogue was erased and the system got restarted" (p.204). In addition, Kaewkannate and Kim [37] show that it is difficult to navigate simultaneously on an app installed on external devices and one installed on wearable devices.

Iconography: The results from the previous studies [51, 75, 80] indicate that an icon allows users to (i) launch an application on devices and (ii) navigate within a user interface to locate functionalities. However, at the same time, the studies on this point out that unintuitive application icons or a poor presentation of the icons on without a text label on an application has a negative impact on the usability. For example, Thorpe et al. [80] show that it was difficult for participants to find a functionality based on the icon's name application on a device user interface. Similarly, Pulli et al. [51] find graphical icons without a label give users more problems when it comes to recognizing their clear association with the function behind the icons in a first-time interaction with the application, for example, a "mobile phone" icon was confused with a "door icon" [51] (p.1125).

Elements (font/button): The results show that the form factor of the devices, such as smaller font size, made it harder for participants to read the devices' screens. For example, Holzinger et al. [59] report that participants wanted to adjust the size of the text when they were not wearing their glasses. Wichrowski et al. [49] also show the suggestions they received about using larger fonts for better readability.

Interaction with the application: According to Carter [82], the usability challenges associated with interactions with the application developed because of too many steps that the user had to go through, which deterred the user from completing the task. Other than issues caused by too many steps, Altenhoff et al. [75] note issues that were influenced by the data provided by the wearable device, which affected the users' first experiences with the application; they further explain that users' first impressions of the application may have lasting effects on user engagement.

Battery life: All wearable devices require higher processing power to accumulate and process data through multiple sensors. In addition, the devices consist of smaller battery sizes that are bottlenecked by the wearable device's shape, weight, and size [23]. In addition, the devices are either integrated with a display or require external devices with Bluetooth connectivity to show processed data. This results in higher battery consumption and limited battery lifetime. Ahanathapillai et al. [83] state that the "hardware used ... is limited in battery life and offers between 5 and 8 hours when used continually ... [this] is recognized as a significant limitation of the hardware" (p.28). Similarly, Sultan [84] points out, "Battery life need to be longer than what is currently available" (p.525). Yang et al. [85] find that an issue with battery life is interrupting data collection, and as a result, devices showed lower quantified-self data, for example, number of steps. Shih et al. [58] and Koskimäki et al. [86] note that issues related to battery life required the user to partake in an additional behavior, such as remembering to charge the device and putting the device on after recharging. For example, Shih et al. [58] state how one participant stated, "It was quite annoying for me remember to wear the device and also to charge it every day" (p.6). Similarly, Thorpe et al. [80] find a higher consumption of battery life impacted older users with dementia because of their challenges in locating the charging port and inserting the cable. In another study, Albrecht et al. [87] find the battery life of smart glasses drained quicker than other devices, such as camera, which was used in parallel during the experiment. They point to the concern of human battery interactions (HBI) [88]. For example, "In medical settings, a cable running down from Glass to an external battery pack may raise concerns with respect to hygiene as well as add potential for Glass to be pulled off the user's nose if something (e.g., a fastener on the physician's surgical gown) inadvertently pulled on this cable" (p.11).

Weight: Although the main aim of wearable devices is to provide users with wearability and portability, the current literature review identifies "weight" as one of the influential usability issues for individuals. Furthermore, the results indicate that the impact of the weight of the devices increased the feeling of attachment among individuals which relates to discomfort [89]. It has also been shown that weight influences device usage. For example, participants in the study of Dhawale and Wellington [24] stated, "Smartwatches to be distracting and bit heavy after a long day of using it" (p.42). Further, Spagnolli et al. [90] assess user acceptance of wearable symbiotic devices and emphasize "... lighter and more discrete wearable devices are better appreciated compared to bulkier and more noticeable ones" (p.96) for individuals.

Memory size: The amount of memory required in wearable devices increases when the device runs a more memory-intense operating system, more applications, and performs heavy tasks (i.e., fetching and parsing data from a cloud or external devices and background apps). Less memory means limitations on the type of applications and tasks that can be performed. According to Oakley et al. [91], when designing applications for low-end devices with slow central processing units (CPU), manufacturers and content providers should consider utilizing comparative textual feedback because these devices may not be able to smoothly process image or video information. Delabrida et al. [54] state that memory events represent the main bottleneck in their experiments.

Aesthetics: Wearable devices that are worn outside the body are considered high-tech devices and fashion accessories [47]. The current literature review identifies, irrespective of age, that this dual consideration impacted usability, which is mainly influenced by aesthetic elements, that is, physical design, color, and materials of the wearable devices during human–wearable interaction. For example, both Rodríguez et al. [71] and Ananthanarayan et al. [76] find that the physical design of the device caused difficulties for participants when attaching the devices to their bodies. Ju and Spasojevic [92] also uncover that the design played an important role for the acceptance of smart jewelry. Similarly, Shih et al. [58] show participants felt the device was cumbersome and intrusive when worn during their daily activities. Ye et al. [74] show how participants also suggested changes with the design, for example, being easily customizable, after using the prototype wearable device. The wearable device's size ultimately determined the degree of daily use. Goto et al. [93] show how participants stated that the size of the watch was one of the constraints that affected its usability; the problem was that the size of the device was inconvenient for users to wear in their daily activities. In agreement with Goto et al. [93], Kondo et al. [94] find that the device size was too large for the participants to use. In other study, Nirjon et al. [95] note how the participants commented that the size of the used wearable ring was larger than a typical ring, making it uncomfortable for all-day wear.

In addition, Abbate et al. [96] show that the shape of the wearable device impacted the usability among participants, here mainly because of the bulkiness and shape of the devices during sleep, which initially made it almost impossible to carry out sleep tests. Abbate et al. [96] state that when they repeatedly modified the device and moved the battery/transmitter, elderly users enjoyed wearing the wearable caps at night. Further, Abbate et al. [96] also suggest that ergonomic and aesthetic modifications would be necessary for improving the level of usability and acceptability, especially in an elderly user population: "… the elderly are attached to a specific aesthetic dress code, characteristic of their likes/dislikes … [they] prefer simple, loose, and comfortable dress, and therefore, the focus should be on a retro style" (p.6). Abbate et al. [96] also find that providing devices in the participants' favorite colors made the wearable devices more acceptable.

Moreover, the current literature review shows that the material and color used on the devices also impacted usability. For example, the wearable devices utilized by [86] for early detection of migraine attacks caused skin irritation among the participants. Similarly, Rodríguez et al. [71] discovers that materials and color applied on the device also impacted usability. In their study, participants suggested the use of different colors or plastic material on the devices. Rapp and Cena [4] find that the color of the tracking devices made it difficult for participants to integrate the device into their daily lives. For example, participants pointed out, "A light blue bracelet could fit with a casual dress for going out with friends, but not with a night dress for formal situations, where she liked more unnoticeable colors" (p.142). In addition, Brun et al. [65] state, "due to the chosen material, the utility stretch straps were judged too small not big enough for some heads, or it could stick with long hair" (p.7), which caused the participants discomfort.

Deployment of Wearable Devices and External Devices

Liu et al. [16] classify each technology by its location on the body. According to Liu et al. [16], "Technology can be on the body (such as wearables), inside the body (such as implants), and carried next to the body (smart phones)" (p.2). Employing a similar classification approach, the issues noted when reviewing the papers were clustered into categories related to the deployment of wearable devices on the body and the corresponding categories: external devices that are carried next to the body (e.g., smartphones). The results of the classification summary are shown in Table 3.

Table 3 Summary of the mapped usability and user interface issues associated with wearable devices related to external devices and deployment of wearable devices on the body (Table representations)

Usability issues categories	Usability issues subcategories
External devices and deployment of wearable devices on the body	Wearing position, motion artifacts, data accuracy, device connectivity, applications installed on external devices

Each of the usability issues related to the deployment of wearable devices, including external devices, are discussed below to clarify how they impacted the use rate.

Wearing position: Wearable devices are either worn on the outside of the body in the form of a watch or on the inner part of the body as an implant. Although the goal of the wearable device is to provide better wearability when the device is worn on different parts of the body, Fang and Chang [97] show that the wearing position of wearable devices impacts individuals' interests, anxiety, visibility, and readability. Similarly, Rodríguez et al. [71] report that when device was worn on the waist during experiment, readability was low. In addition, other studies emphasize that performing a task could be impacted by the wearing position. For example, Carter et al. [82] note how it was difficult for participants to interact with an application to type with the watch hand and difficult to lift the arm to view the screen. Additionally, Chen et al. [79] say that although individuals had accurate results from their physical activity while using wearable devices, such as pedometers and accelerometers, when the devices were worn on the waist, they had difficulties during toileting and dressing. Zhang and Rau [69] also report that many participants could not see the content on the watch clearly when jogging because of body vibration and distortion. Moreover, Nirjon et al. [95] state that when using a wearable ring, placing the fingers and palm flat on a surface impacted the user while typing.

In addition, there are usability issues from the wearing position that are caused by a halo-effect between the individual and device characteristics. For example, in the study by Rodríguez et al. [71], participants indicated that where the device was positioned on the waist did not adjust to meet heavier body types: "I am bigger and fat" (p.8). Mizuno and Kume [98] observe a similar pattern while evaluating a glasses-like wearable nasal skin temperature measurement device: "For some test subjects, differences in the distance from the thermopile sensors attached to the glasses and the nose or forehead caused by head or face shape variations prevented appropriate measurements" (p.730). Similarly, Yoo et al. [99] note that devices such as a watch or a wristband, which can be worn on the wrist or waist (e.g., abdominal binder), are more easily accommodated than a head-worn device. For example, they state "the head is hardly suitable for patients because they don't frequently wear even a hat" (p.364).

Motion artifacts: To recognize users' activities while at a state of rest or in motion, wearable devices are embedded with a network of sensors; here, designers make the assumption that the device is worn in the predetermined orientation position relative to the individual's body [100]. However, the predetermined position may gradually change because of an incorrect wearing position or wrong body movements while at a state of rest or in motion. Although motion artifacts do not have a direct impact on the individual, the current study shows that motion artifacts have a usability effect through the quality of data delivered, that is, through inaccurate data. For example, Ahanathapillai et al. [83] measure the parameters from an accelerometer on the wrist as an indicator of wrist movements. The results show that the measurement changed from medium to high with lots of wrist movement, rather than a recording of low activity data. Moreover, Ahanathapillai et al. [83] also report the presence of motion artifacts because of the movement of the fingertip of the subject, which, in this case, may have produced inaccurate heart rate measurements. Similarly, Klingeberg and Schilling [101] also find arm movements caused distortion on pressure signals. In other study, Chen et al. [79] report that the number of steps captured by wrist-worn devices was more than the participants actually walked, stating that this may have been “because that the wearable device used in this study took into account the arm movements. Therefore, it is unclear how much counts come from walking” (p.37).

Data accuracy: Wearable devices capture and provide digital data, such as quantified-self, image, location, audio, and video with the help of embedded sensors and camera. Those data are either used by individuals to monitor their activities or track their health conditions for their well-being or for entertainment purpose. However, the literature review shows that usability is disrupted by a deluge of inaccurate data caused by (i) motion artifacts; (ii) device connectivity; and (iii) physical conditions. For example, in the study of Liang et al. [102], the participants reported wrist-worn devices were shown to be “asleep” while “reading,” causing “issue of trust” among users. Altenhoff et al. [75] observe that participants had problems trusting sleep data after the first night a device failed to accurately report the time they fell asleep. In the same study, one participant was surprised when upon first syncing the band and app, the app displayed about 80 steps before she had taken any actual steps, which she then commented on the third day, “I feel like I would just use it when working out to figure out what I’d actually done and for sleep but not walking because it’s not accurate” (p.244). One participant in a study by Kaewkannate and Kim [37] responded, “the display to check the tracking status requires a smart-phone. Sometimes, data are inaccurate because of lost syncing to the smartphone” (p.8). Masai et al. [103] report that sensor data were saturated when the sensors were exposed to ambient light, that is, sunlight, which caused a smart eye wearable to deliver incorrect data of the wearer’s facial expression.

Device connectivity: Most wearable devices do not include a built-in global system for mobile communications (GSM) or a global positioning system (GPS) module; they often pair with external devices such as smartphones or a computer using Bluetooth or Wi-Fi to exchange data and deliver relevant information. However, the results from the review show that the initial pairing between devices is either difficult, or when paired, the connectivity is unreliable. For example, Wichrowski et al. [49] study Google Glass and had problems pairing the wearable with smartphone devices via a Bluetooth connection. According to Wulf et al. [81], a steady and reliable Internet connection could substantially increase the usability for speech-only interactions for wearable systems; this unreliable connectivity resulted in inaccurate data. Similarly, Kaewkannate and Kim [37] report that the automatic loss of synchronization between wearable and external devices made it difficult to update data or resulted in inaccurate data. This demand for a connection impacted the usability of users. Moreover, Thorpe et al. [80] observe that the Bluetooth connection between the wearable and external device dropped unexpectedly, requiring participants to reset the wearable device. Further, Rasche et al. [73] observe that even though the necessary graphical interface was integrated into the app, the installed application on external devices demanded a Bluetooth connection, which was difficult to handle for most participants.

Application installed on an external device: The literature review shows that because of technological and design challenges, the wearable devices used in the previous study mostly work in parallel with mobile devices. For example, when a certain action is performed on wearable devices, such as fitness tracking, the reaction is displayed on an application installed on a mobile device. However, the current analysis shows that having to use applications installed on external devices imposes higher mental effort and stress for users because of concerns related to interruption, installation, and actions that must be performed. For example, Ananthanarayan et al. [76] find that with smartphones as the external device, participants were concerned about being interrupted by texts and phone calls, losing focus, and having to prop up the phone for a better viewing angle. Rasche et al. [73] observe that participants needed to maintain a higher mental effort to install the app on external devices and get the activity tracker to work. Rapp and Cena [22] show that one participant became stressed about the action she had to perform to view the data, for example, "take out the phone, open the app, and explore the graphs and numbers, which she termed 'a laborious task'" (p.141). In another study made by Dhawale and Wellington [24], participants indicated concern regarding having an application on the external devices and viewing this application while performing a physical activity because of what the participants perceived as risk associated with the device screen getting damaged. In addition to this, Kaewkannate and Kim [37] evaluate wearable devices with an application installed on the external devices, and they emphasize the usability concerns related to interacting with the application that is installed on external devices, for example, difficulty with using the food log and calorie tracking tool in the user interface (UI) of the application.

In summary, following Ally and Gardiner [43] and Liu et al. [16], the categorization resulted in 18 issues related to the device characteristics, including shared issues between UI fundamentals, three issues related to the deployment of wearable devices on the body, and three issues related to external devices, in which data accuracy is added separately to each category. Although all categories were important, analysis shows that issues associated with the deployment on the body, external devices, and physical (i.e. aesthetics) have the most influences on user interaction.

Combining the identified usability issues, it is useful to understand and assess the relationship between the usability issues related to the device characteristics, deployment of the wearables on the body, and the use of external devices; to do this, the constructed categorization framework is given in Fig. 5, which combines a total of 20 usability issues and gives the holistic view of overall usability issues that currently exist in all type of wearable devices. Furthermore, the categorization framework clearly shows that some of the usability issues related to the wearable

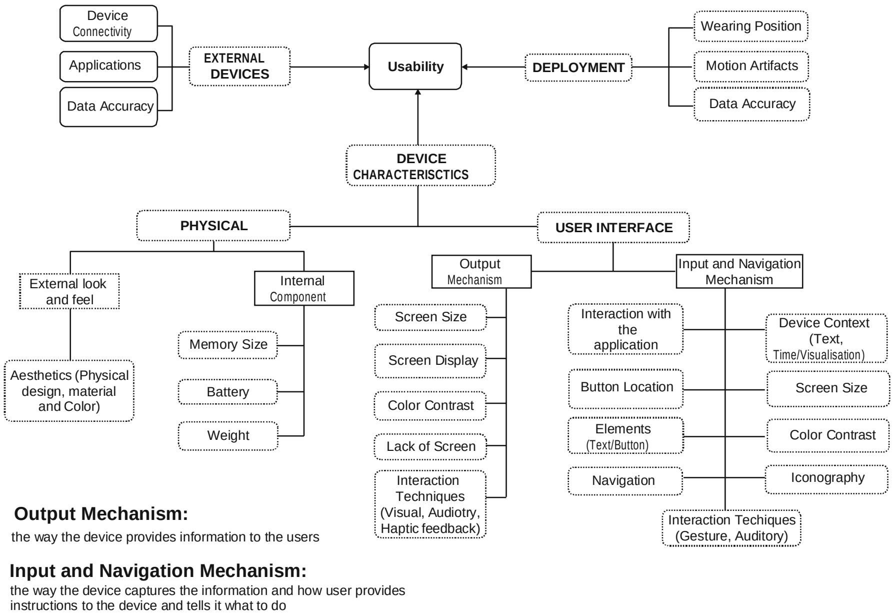

Fig. 5 Usability issues categorization framework based on the reviewed paper

devices share common themes across other categories (Fig. 5). For example, both device connectivity and deployment share the cause of data inaccuracy.

However, the categorization framework does not show which type of issues categories and subcategories is related to what type of wearable device. Therefore, the categorization framework was further reviewed in relation to the wearable device categories presented in Table 1. Table 4 provides the overview of each type of wearable device category, usability issues categories, and subcategories and associated usability issues.

4.2 Q2: How Have Usability Evaluation Methods (UEMs) Been Applied to Wearable Device Evaluation and in which Device Categories?

This section summarizes which evaluation methods have been applied to identify the issues discussed in Sect. 4.1. To answer the first part of RQ2, the methods reported in the primary studies were analyzed and grouped into a taxonomy, as proposed by

Table 4 Summary of the usability issues based on the categorization framework in Fig. 5

Usability issues categories and subcategories			Associated usability issues	Device categories																		
				Smart watch	Smart wig	Smart clothing	Smart ring	Smart jewelry	Smart shoe	Smart bracelet	Wristband	Arm band	Smart headband	Smart headphones	Inertial sensor pack	Activity tracker/monitor	Wearable tele-echography robot	Head-worn terminal/body motion monitor	Smart knee support	Chest-mounted devices	HMD with binocular (worn over both eyes) opaque or transparent, for example, AR	HMD with monocular (worn over one eye) transparent, for example, smart glass
External devices			Data accuracy	X												X						X
			Applications			X			X							X			X	X		X
			Device connectivity	X							X					X					X	X
Deployment			Data accuracy	X							X					X						X
			Motion artifacts	X							X		X		X	X					X	X
			Wearing position	X	X	X	X	X	X	X	X	X				X	X				X	X
Device characteristics	Physical	ExternalLook and feel	Aesthetics (physical design, material, color)	X	X	X	X		X	X		X	X			X		X	X		X	X
		InternalComponent	Weight			X										X					X	X
			Battery	X		X						X				X					X	X
			Memory size	X											X						X	

	User Interface	Input and navigation mechanism	Iconography	X						X						X				X		
			Color contrast																			X
			Screen size													X						
			Device context (text, time/visualization)	X		X				X	X					X			X		X	X
			Navigation	X							X					X					X	
			Elements (text/button)	X							X					X		X				
			Button location	X							X					X					X	
			Interaction with the application	X						X	X					X					X	X
			Interaction techniques (gesture/auditory)			X								X		X					X	X
		Output mechanism	Interaction techniques (visual, auditory, haptic feedback)							X	X				X	X		X		X	X	X
			Color contrast								X										X	X
			Lack of screen													X						
			Screen display	X												X		X			X	X
			Screen size	X						X						X					X	X

Ivory and Hearst [36]. Accordingly, the UEMs can be grouped into four dimensions, as follows:

Method class: This comprises the method, such as usability testing and simulation, and is entirely conducted at a high level. This usability evaluation method can be further classified into the following five classes [36]:

- *Testing:* With the intent of finding the usability issues, an evaluator watches user while they are using the evaluated applications/devices.
- *Inspection:* An evaluator creates and utilizes a set of evaluation guidelines or heuristics to assess the possible usability issues related to applications/devices.
- *Inquiry:* The extent to which users share their usability experiences with the evaluators regarding the evaluated applications/devices via methods such as interviews or surveys is examined.
- *Analytical modeling:* This is the degree to which an evaluator predicts the usability issues of the evaluated applications through modeling tools.
- *Simulation:* This is the extent to which an evaluator discovers the usability issues by deploying simulation tools of the applications as if the user is interacting in reality.

Of these five method classes, "testing, inspection, and inquiry are suitable for both formative evaluation" [36] (i.e., the evaluator identifies specific usability problems that are already known before conducting the evaluation) and summative evaluation (i.e., the evaluator obtains general evaluations of usability) purposes, where there are "analytical modeling and simulation" are appropriate for the performance evaluation of users.

Method type: This represents how the usability evaluation (UE) is performed under the method class and with a range of UEMs, such as performance measurement and think-aloud.

Automation type: This represents the use of highly automated techniques for the UE in which a software tool is utilized to simulate the user's action in capturing the data, for example, the software tool automatically records the usability data by logging the user interface usage [36], analyzing it (i.e., the software installed on the devices automatically records usability issues), and critiquing it (i.e., the software installed on the devices analyze the usability issues and suggest improvements).

Effort level: This is the level of human effort required while executing the UEM dimension (method class and method type). The effort level can be (i) minimal effort (MF) (i.e., does not require interface usage); (ii) formal use (F) (i.e., requires completion of specifically selected task); (iii) informal use (IF) (requires the completion of a freely chosen task); or (iv) model development (requires the evaluator to develop the UI model to employ the method) [36].

Table 5, which represents the answers to the second part of RQ2, contains wearable categories, usability evaluation method type (UEMT), usability evaluation method class (UEMC), automation type, and effort level. As shown in Table 5, a

Table 5 Studies reporting the use of each evaluation method

Usability evaluation methods		Device categories																				
Method class	Method	Automation level	Effort level	Smartwatch	Smart wig	Smart clothing	Smart ring	Smart jewelry	Smart shoe	Smart bracelet	Wristband	Arm band	Smart headband	Smart headphones	Inertial sensor pack	Activity tracker/monitor	Wearable tele-echography robot	Smart knee support	Head-worn terminal/body motion monitor	Chest-mounted devices	HMD with binocular (worn over both eyes) opaque or transparent.	HMD with monocular (worn over one eye) transparent.
Inquiry	Interview	N	F, IF	x	x	x				x	x					x					x	x
	Questionnaire	N	IF	x		x	x	x	x	x	x							x	x		x	x
	Diary	N	IF					x			x					x						
	Survey (pre-post)	N	F	x		x					x		x			x					x	x
	Observation	N	F	x				x		x							x				x	
	Self-reporting logs	C	F			x															x	
	User feedback	N	IF			x					x											
	Focus group					x			x		x					x						x
Testing	Think aloud protocol	N	IF													x		x				
	Log file analysis	N, C	M, F	x	x		x				x				x	x			x	x	x	
	Performance measurement	N, C	IF, F	x							x			x		x	x		x		x	x
	Question-asking protocol	N	IF								x											
Inspection	Feature	N		x																	x	
	Perspective based	N																	x			

review of the 84 studies revealed that 78 studies did include a UE. In the studies, 14 different method types were applied to understand the usability of the 19 types of wearable device categories. Regarding the automation type, three studies apply the application to record the usability data (C), and others do this using an evaluator with either freely chosen task or specific selected task without any level of automation supported (N). The literature review indicates that the studies have adopted effort level (i.e., formal use, and informal use, model use). To gain an overview of how the UEM type was conducted within a method class, the obtained method types were grouped based on five method classes. After grouping, three method classes were identified: inquiry, inspection, and testing. However, the results show that none of the studies applied analytical modeling.

More specifically, we can see from Table 5 that out of 14 obtained evaluation method types, 41 studies adopt multiple evaluation methods to gather multiple sources of data to get a better overview of wearable devices from the users' perspective. In most of the studies, the interview UEM type was applied during usability evaluation sessions. For example, Altenhoff et al. [75] apply multiple evaluation methods, including think-aloud, post-survey, and interviews (i.e., unstructured), to evaluate two different activity trackers and their associated applications. The think-aloud protocol allowed participants to speak and perform the task by, for example, setting up an activity tracker device and its associated application, allowing the evaluator to collect data such as time-on-task and average error. To gather the overall experience of the device usage, and eliminate the issues of reactivity, participant's verbal abilities, and validity [104], researchers further apply additional usability methods, such as a through post-survey and interview.

Additionally, Rasche et al. [73] evaluate the usability of the activity trackers by utilizing DIN ISO 20282-2 and applying the think-aloud protocol. Because the think-aloud protocol itself cannot grasp the mental effort of the participants, the researchers adopt the Rating Scale of Mental Effort (RSME) unidimensional instrument. Moreover, Rasche et al. [73] use interviews and different questionnaires; first, the Post Study System Usability Questionnaire (PSSUQ) is used at different times to understand the participants' attitudes about the product and changes in perceived usability [105]; the MeCue questionnaire is also used "to evaluate the perceived aesthetics of the activity tracker, the stigmatization of using it, the wearing position, and the intention of usage" (p.1412); a technical affinity questionnaire is used to understand if technical affinity changes during the process of getting used to the application by participants. In summary, having different questionnaires allowed the researchers to gather data from different angles and understand the participants' attitudes toward usability, requirements, motivation, mental effort, and technical affinity of activity tracker. Additionally, Fang and Chang [97] use a pre-test questionnaire to finalize the contents of the formal questionnaires.

On the other hand, the current study also identifies that the type of experimental tasks and period of use of devices also influences how users perceive the hedonic and pragmatic values of the evaluated devices or user interfaces [50]. In the reviewed papers, the researchers who adopted longitudinal usability testing with informal use collect more data to understand what effect the adoption of the device or user interface has. For example, Shih et al. [58] gather the logs of the usage data from activity trackers, collecting the usage pattern and issues of remembering, physical design and aesthetics, data management, integration and sharing, and data accuracy. Lazar et al. [6] discuss the advantages of conducting a long-term usability evaluation with a freely chosen task and selected device while conducting the interviews later, here stating, “By allowing participants to choose devices and then interviewing them several months later, we were able to see the ways people integrated devices into their lives or abandoned them and the factors for doing so” (p.644).

Apart from the adoption of multiple usability evaluation approaches, not all the usability evaluation method types are suited for individuals with impairments. For example, Kashimoto et al. [106] apply the Wizard of Oz method with unstructured interviews during the iterative usability test for the development of a smart glass prototype. During the evaluation, Kashimoto et al. [106] find it was difficult for older adults with dementia to stay in a stationary position for a long time, focus, and accomplish the navigational task, which resulted in the researchers gathering unsatisfactory data for further analysis. However, the qualitative data were gathered through interviews. All the methods are also not suitable for participants with a minimal education level. For example, Sin et al. [107] apply four usability constructs that is, ease of use, efficiency, effectiveness, and user satisfaction, to evaluate their prototype. While collecting the data to measure the system’s usability through a system usability scale (SUS), the researchers find the participant’s had a lack of formal education, and as a result, all the questions had to be read by “the researcher, and they only were asked to point their answer on a graphical Likert scale” (p.124).

5 Findings and Recommendations

In addition to usability issues, the current study revealed additional findings, especially regarding the (i) social-technical aspects, (ii) effect of usability, and (iii) individual preferences of wearables. For example, the study conducted by Bower and Sturman [108] finds that participants were concerned about the privacy of people taking their photos and recording videos of them. Although, an interaction technique facilitates the user experience, similarly, Ye et al. [74] show that the interaction technique also brings social-technical challenges. For example, in their study, participants had difficulties using speech as the interaction techniques in a public environment because of privacy concerns. Similarly, in the study of Wulf et al. [81], some of the older adults were concerned about using speech interaction in public and felt uncomfortable doing so. We also found that a barrier, such as a design flaw on the physical design of the device or implementation bug on the user interface, causes frustration, fatigue among individuals with impairments at faster rate than with individuals without impairments [62]. Similarly, in another study conducted by Wulf et al. [81], the emotions of the users’ reactions changed when the speech interaction did not function properly. Angelini et al. [109] also find that older adults have different preferences of the devices, stating, “The medical feature should not emerge in the product and should be presented as an accessory feature, which, however, will be appreciated by their relatives" (p.431). Similarly, Ye et al. [74] show that the aesthetics aspect of the device is relatively important for visually impaired participants.

Although we provided a comprehensive overview of the usability issues through a categorization framework and category summary (see Table 4), the literature review shows that these identified issues are still unsolved and need immediate attention from technology designers, researchers, and application developers. In this section, we discuss some of the obstacles, including design; individual preferences; device usage; and data, that are causing the identified usability issues and have been discussed and need further investigation. Furthermore, these challenges still persist because some aspects of the characteristics of wearable devices, such as the wearing position, do not satisfy an individual's daily hedonic or utilitarian (practical) needs, affecting their emotions, personal taste, self-expressive dimension (social and altruistic value), aesthetic, and functionally related values [110–112].

The SLR shows that background of wearable devices is becoming increasingly heterogeneous because of the rapid rise of (i) several categories of wearable devices, such as smartwatches, pedometers, implants, and HMDs and (ii) an embracing of the culture for monitoring, tracking, delivering, augmenting, and assisting purposes in both one's personal and work environment [1]. In addition, one of the insights gained from the SLR is that the usability issues surrounding the user interface, product aesthetics which can degrade user performance and user dissatisfaction [113], are related to the attributes of the user's characteristics, such as age and the user's background [74, 114]. Designing the user interface (i.e., visual interface and non-visual wearable interface) and the product aesthetics for wearability, accessibility, and readability which fulfills attributes of user's characteristics poses trade-off challenges to both device manufacturer and the application developers. Although many researchers try to offset these issues through with user-centric design approaches [67, 80] or by applying universal design principles and guidelines [15, 23, 115, 116], challenges still persist. Gandy et al. [15] state, "making devices that all individual can access at all times isn't always possible" (p.19). For example, we believe that these challenges persist because the design guidelines are usually created based on the individual's characteristics, such as age and disability, without looking at the individual's daily different use contexts and the device form factors. Kim et al. [117] state that, "Different usability problems are experienced more often according to different use contexts" (p.9). Because wearable devices can be utilized in various use contexts within the work environment and home and because they have versatile input systems in various form factors, including smart clothing, ring, necklace, wristband, and on the body [118], it is critical for research community to find ways to overcome future challenges.

Although one of the major goals of wearables that depend on sensors is to mediate the experience of reality between the individual and data and develop an intimate relationship between them [119], when either one or multiple wearables are connected to a single hub, that is, an external device, and the information is delivered using a single user interface on the external devices, a challenge arises regarding the data quality standard (i.e., availability, usability, reliability, relevance, and presentation quality) [120]. For example, the SLR reveals that the data quality standard is obstructed by suboptimal app crashes; poor synchronization of data because of a lack of connectivity; and motion artifacts. Looking closer at this challenge, the impact of data quality will have a significant implication for user experiences [121], more negative and arousing subjective feelings of excessive self-monitoring, a false sense of security, or may fuel a self-driven misdiagnosis [10] that can demoralize users' emotions, ability, and motivation, impacting the success of the applications. For example, Fogg [122] asserts that for behavior to happen, a person must have sufficient motivation, sufficient ability, and an effective trigger. Similarly, Zadra and Clore [123] point out that emotions can routinely alter the perceptions of individuals, here stating, "positive moods encourage one to maintain one's current way of looking at things, and that negative moods encourage a change" (p.10). To improve the quality of the data from the app, utilizing the early prediction approach for application crashes presented by Xia et al. [121], which is based on a naive Bayes model, before releasing the apps to the individuals should be considered. Similarly, the research community and technology designers should consider looking for techniques to improve the usability challenges regarding the poor synchronization of the data. One way is to use future complementary wireless networking techniques, such as "light fidelity (Li-Fi)" or "data through illumination (D-light)," which both provide additional free and vast wireless capacity, along with the ability to enhance the spectrum efficiency of existing radio frequency (RF) networks [124]. Although Li-Fi requires light to pass through the device, this technique could be implemented in wearable devices such as smartwatches and pedometers, which have a user interface and could easily interact with the light for data transmission, hence improving communication, speed, flexibility, and usability [125]. Similarly, another way to improve the quality of the quantified data is by reducing the impact of the time discrepancies in the data itself, which usually occur during the data fusion from multiple wearable devices converging with the external devices. Here, either model presented by Xu et al. [126] can be applied: a single-modal normal distribution (SMND) model for devices in which the data are generated with static frequency, for example, heart rate data, or a multi-modal normal distribution (MMND) model for devices in which data are generated with a dynamic frequency, for example, the step data collected by a smartwatch. Although we discussed improving the data by reducing the time discrepancies and using complementary wireless technology, looking closer, the main issue still remains when it comes to motion artifacts because of predetermined and orientation positioning relative to the individual's body [100], sources of nuisance, such as measurement noise [127], and failure to recognize activity by the sensors. We suggest that technology designers and researchers should consider utilizing the K-nearest neighbor (KNN) and its ensemble classification method with a proper choice of key parameters. This will have significant impact on the recognition accuracy when it comes to designing a robust and responsive machine learning in the wearables, as described by [40].

Beyond the user interface and data challenges, the additional major challenges that the SLR shows with regards to current device manufacturers face in understanding the individual preferences and device usage such as which sort of device shape and size, material do individual prefer; preferred position to wear the device, are those devices utilized for tracking physical activities, adopted as fashion accessories or used for educational or entertainment purposes. Abbate et al. [96] assert, “Ergonomic and aesthetic modifications are necessary to improve the level of usability and acceptability” (p.231). One way to move forward is to improve the design of the product’s aesthetics, making them unique in their design, keeping them lightweight, choosing materials that depend less on the internal components and instead using a modular-based approach where individuals can change the device’s external look and feel based on their daily needs. The question is then how to design a device that is more lightweight than what is available now. One possibility could be reducing the battery size and increasing battery life by (i) utilizing the work presented by Shen et al. [128], which is based on graphene-based supercapacitor fabrics with a high energy density and load-bearing capability or by (ii) harvesting energy from alternative sources, such as heat and motion from the body in the form of kinetic or thermal energy [129]. In addition, implementing these techniques would not only improve the weight, but also reduce the charging inconvenience [130], improving wearing behavior and ultimately leading to long-term use.

In the future, when more wearable devices such as HMDs are utilized for daily use purposes, more challenges with the visual interface design will appear, especially with the “output,” that is, how much information will be delivered to the user and for which type of devices. For example, delivering information on the screen display of a HMD may not be the same as delivering information on smartwatches or external devices because information on a HMD will create a visual distraction and further complexity. In addition to delivering information, other challenges are the usage modes with wearable devices, the user interface, and the wearable’s associated applications on external devices. For example, when multiple wearable devices become part of the user’s daily life, the user will have different usage modes, such as sequential usage (i.e., moving from one device to another at different times to accomplish a task) or simultaneous usage (i.e., using more than one device at the same time for either a related or an unrelated activity) [131]. This could cause challenges related to usability, learnability, effectiveness, efficiency, memorability, errors, user satisfaction, task-technology fit, accessibility, orientation clues, conciseness, and cognitive load [132–134].

To conclude, the categorization framework and category summary (see Table 4) show that the usability challenges related to wearable devices are well known in the human–computer interaction (HCI) field; however, one could argue that these challenges still persist because the research community within the HCI field is focused on identifying and solving problems by conducting usability evaluations, using less targeted participants who are within a specific geographic location, rather than understanding the emotions and perceptions of larger groups of individuals, applications from a demographic context (e.g., age, gender, impairments, education level, employment status, and culture) [135]. Moreover, device manufacturers (i) are more focused on horizontal innovation, which solely implies changes in the current product characteristics; and vertical innovation, where new additional features are implemented, or the technical characteristics are improved to compete with other device manufacturers [136]; (ii) sponsored validation tests which may not be independently verified and may be difficult to understand and replicate individually [70]. Additionally, application developers are more focused on developing applications without understanding the users' needs. For example, commercial off-the-shelf (COTS) wearable devices are mostly designed by the designer, who is located in a specific location, who does not have knowledge of other culture, and who simply localized user interface based on the translation. Similarly, application developers create an application in one geographic location and target it to different locations through the application store. Although this allows device manufacturers and application developers to release their products to be used everywhere, sometimes with support and special features for use in a specific locale [137], issues arise from the cultural context, including the "anthropological culture," "symbolic culture," and "culture as community" [138]. Smith and Yetim [139] state, "Effective strategies that address cultural issues in both the product and the process of information systems development now often are critical to systems success" (p.2). In considering how to increase the adoption of wearables by individuals, future research should incorporate greater variations of larger groups of individuals to analyze their emotions, and perceptions toward existing wearable devices within a certain demographic context (e.g., age, gender, impairments, education level, employment status, and culture) [135].

On the other hand, most of the reviewed papers perform usability evaluations with devices that are in the prototype phase or with devices that are already available on the market. Usability evaluations throughout the design cycle of product development are critical to ensure that the products are usable. There is currently no usability evaluation method for detecting and mapping usability issues from the initial stage of the development process of wearable devices to their release. Because wearable devices need to be reliable and wearable, the traceability of the usability evaluation together with users from different demographic contexts is crucial during each further stage of the development process to identify user needs and eliminate usability issues. Further research should be oriented toward identifying possible usability evaluation methods and integrating effective usability evaluations into the wearable development process. The results obtained from each usability evaluation can thus be effectively evaluated to ensure the reliability of the wearable devices to create commercially viable devices. There are different categories of wearable devices, as well as usability evaluation methods.

The limitations of the current study relate to its reliance on the articles from previous research and the inclusion and exclusion criteria. In addition, the search keywords were limited to "usability issues" when "wearable devices" was the targeted keyword. However, access to relevant papers depends on the precision of the search strings. Because the current study only concentrated on the abovelisted search keywords, it is possible that other relevant articles could have been retrieved with different sets of keywords. The search also produced non-relevant articles and low-quality publications that were ignored. In addition, the main search was conducted only in English, which limits the results and maximizes bias.

6 Conclusion

In different product forms, wearable devices are appearing rapidly in the market, but the usability of them is challenging. Although many studies conduct a usability evaluation, a comprehensive overview on which types of usability issues currently exist for which types of devices is lacking. The uniqueness of the current work is in it filling this gap by identifying, analyzing, and providing a comprehensive overview of current trends of usability issues found in relevant studies. The review has revealed that in current research, usability challenges related to wearable devices can be categorized into device characteristics, deployment on the body, and the external devices used to synch with the wearables. In many cases, the usability issues are caused by a halo effect within device characteristics or device characteristics and wearing position. For example, data inaccuracy is caused by motion artifacts or by device connectivity.

Overall, the proposed categorization framework and category summary (see Table 4), of the usability issues generated from prior studies shows researchers, practitioners, and application developers in the wearable domain what challenges they have to consider to improve the design of the various types of wearable devices. Although the presented categorization framework, and category summary (see Table 4) provides an overview, there are still challenges that must be overcome in terms of design; individual preferences [140]; device usage; and data, all of which are causing the identified usability issues. Improving these open challenges will likely improve the adoption of wearable devices, however requiring to strengthen coordination between researchers, practitioners, and application developers. Additionally, the current study identified the most frequently used evaluation methods (i.e., types and classes, automation, and simulations) utilized for measuring the usability of wearable devices. It was found that experiments, surveys and questionnaires, and interviews were the most employed UEMs type and that inquiry was the most common UEM class. Moreover, the summary (see Table 5) provides an overview that can be used by practitioners and application developers to understand and make decisions while selecting the UEM for a particular type of device evaluation.

The present study can, however, be used as a basis for further studies to (i) extend new usability issues for upcoming wearable devices; (ii) discover how a categorization framework of usability issues varies across different demographics (i.e., age, culture, and gender); (iii) quantitatively identify the predominant usability issues from the proposed categorization framework; and (iv) extend usability evaluation method for new type of wearable devices.

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