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Explore the Ideal Human Body Part for Medical Wearable Sensors

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Abstract: Wearing wearable devices has become a part of daily life for many people worldwide. Wearables provide various applications, including health monitoring, diagnosis, treatment, and rehabilitation. Since wearable devices are in close contact with the human body, considering human factors aspects during the design and development stages is essential for the success of future wearables. This research aims to assess the optimal body part for medical wearable sensors' placement based on the wearable's expert opinion questionnaire. The study focused on four main categories: cardiovascular monitoring, neuromuscular monitoring, biofluids, and gait disorders, considering three placement criteria: comfort, accuracy, and simplicity. Corresponding to the findings, there is a gap between the recent research outcomes and the experts' answers. In particular, the answers to the questions related to the placements of wearable sensors for neurological and gait disorders were limited to the traditional clinical diagnosis techniques. This could be attributed to insufficient knowledge and collaboration between engineers and medical professionals. This highlights the need for a systematic way to evaluate the wearability of wearables based on their performance alongside wearability criteria by establishing a wearability assessment human-centric framework for each wearable sensor application supported by clinical studies and experimental data, which could reduce the time for development and commercialization of accurate, reliable, and comfortable wearable medical devices.

Keywords: medical wearables, cardiovascular diseases, neurological disorders, wearable sensors

1. Introduction

The applications of wearable technology have been increasing rapidly in the last few years, driven by the latest advancements in smart sensors, additive manufacturing, augmented reality, and data analysis [1, 2]. Wearable technologies support a wide range of applications, including health monitoring, treatment, rehabilitation, activity recognition, and fitness [3]. These applications pave the way for the development of innovative wearable devices and practical solutions aimed at enhancing users' quality of life worldwide. For example, recent advancements in Artificial intelligence (AI) and blockchain have significantly influenced wearable medical technologies [4]; given that microstrip antennas have shown promise in improving signal fidelity in body-worn IoT applications, future research should consider integrating such innovative approaches for enhancing the wearability of medical wearable sensors [4]. Currently, wearable devices are available in several different forms in the market, such as accessories (smartwatches, wristbands, smart eyewear, headsets, smart jewelry, and straps), e-textiles (smart garments, foot-worn, and hand-worn), and e-patches (sensor patches, e-tattoo, and e-skin) [5, 6]. Accordingly, since wearable devices are in direct contact with the human skin or fluids, taking human factors aspects into consideration during the design and development stages is an essential part of the success of future wearables and cannot be neglected. Therefore, criteria such as weight and dimensions, comfort, simplicity, and user-friendliness should be considered alongside other hardware and software aspects [7]. Many of the placement preferences observed in this study align with fundamental human factors principles. For example, discomfort associated with the wrist and neck can be attributed to high mobility, soft tissue deformation, and sweat exposure. In contrast, higher chest and upper arm ratings reflect these regions' relative stability, flatness, and lower flexion. These patterns suggest that expert preferences are influenced consciously or not by ergonomic and anthropometric considerations that affect sensor adhesion, comfort, and performance.

Utilization of optimal placement could expedite the generation of more efficient and comfortable wearable devices that give more attention to human body parts characteristics while maintaining the satisfactory accuracy required by the application.

Furthermore, this study will highlight any knowledge gap and different perspectives between experts from different professions (e.g., engineering, medicine, nursing, chemistry, biology, and business management) regarding medical wearables and propose a coordinated and unified wearables manufacturing strategy.

Despite the rapid miniaturization of wearable technologies, which has enabled seamless integration with the human body, a persistent paradox remains: smaller does not necessarily mean better when it comes to sensor placement. These devices' comfort,

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accuracy, and usability are still highly dependent on where and how they are worn. This study challenges that paradox directly by empirically examining expert insights on optimal placement across various sensor types, revealing that even the most sophisticated sensors are constrained by fundamental human-centered design considerations. This study defined comfort and simplicity as subjective constructs evaluated through expert judgment. Comfort refers to perceived ease of long-term wear, including friction, sensor movement, and expected skin irritation. Simplicity relates to ease of donning and doffing, placement visibility, and expected user compliance. Furthermore, accuracy refers to the closeness of the measurements to clinical-grade performance, as judged by experts.

This research uses an expert opinion questionnaire to determine the optimal human body part for medical wearable sensor placement. The study will address four main wearable sensor categories: heart and blood vessel disease monitoring, nervous system disease monitoring, gait disorders, and body biofluids and microfluidics, and will take into consideration three main placement criteria: comfort, accuracy (closeness to the true value), and simplicity. All participants had published research on the design, development, and manufacturing of medical wearables.

2. Methods

2.1. Ethics and informed consent

This study used an online self-administered questionnaire in the English language. The data was collected between August 2023 and September 2023. Individuals who have published research in medical wearables were targeted. The participants gave electronic consent at the beginning of the survey. The survey started by briefly describing the research and its purposes, indicating that participation is completely voluntary, their responses are completely anonymous, and they can skip any questions. Moreover, to protect your privacy, they should avoid using shared devices and make sure to close their browser after survey completion. Researchers' contact information for questions and eligibility criteria to participate were also presented within the survey. The institutional review board of Iowa State University approved the study protocol as an exemption research where the individuals' identities were not ascertained directly or through identifiers linked to the subjects.

2.2. Instruments

The survey was developed to cover the main wearable sensors categories: heart and blood vessel diseases monitoring, nervous system diseases monitoring, body biofluids, and gait disorders, addressing, at the same time, three main placement criteria: comfort, reliability, accuracy, and simplicity. Recruitment emails attached with the online questionnaire and a Qualtrics survey link were sent to the potential responders. Participants were selected based on their expertise in the development, clinical use, or research of wearable medical technologies. Inclusion criteria required participants to have a recent publications on this field and had to declare themselves as an expert in at least one of the following areas: cardiovascular diseases (heart and blood vessel diseases), neurological disorders (nervous system diseases), body biofluids (blood and sweat), and gait disorders (walking and balance problems); then, the responder can voluntarily answer specific questions depending on their areas of expertise. Finally, their response was recorded automatically. The final version of the survey consisted of four sections. The first section collected demographic and general information about gender, age, education level, profession, and areas of expertise. The second section showed the responders the human body parts' figure, which gave them the flexibility of choosing the appropriate level of specification while determining the proper body placement of each wearable sensor according to each placement criterion. The third part was determined for each responder based on their previous answer for the area of expertise question in section one. For example, if the responder's answer to the area of expertise question was cardiovascular diseases (heart and blood vessel diseases), the third section was related only to the placement of the related cardiovascular diseases' sensors. Figure 1 and Table 1 show the human body parts in the survey and the demographic characteristics of the participants, respectively. The participants answered specific questions related to each wearable sensor as follows:

1) Which human body parts do you associate with sensing heart rate in terms of comfort?

Figure 1
Human body parts

Head	Scalp	Crown	
	Face	Forehead	
		Temple	
		Eye	Pupil
		Nose	Nostril
		Cheek	
		Mouth	Lip
			Tongue
		Ear	Earlobe
		Nose	Nostril
		Chin	
Neck	Nape		
Shoulder			
Armpit			
Trunk	Chest	Breast	
	Back		
	Waist		
	Abdomen		
Buttocks			
Hip			
Upper Limb	Upper arm		
	Elbow		
	Forearm		
	Wrist		
	Hand	Palm	
		Fingers	Thumb
			Index finger
			Middle finger
			Third finger
			Little finger
Lower Limb	Thigh		
	Knee		
	Leg	Shin	
		Calf	
	Ankle		
	Foot	Heel	
		Instep	
		Toe	

Table 1
Demographic and general information about the participants

Demographic factor		Percent
Gender	Male	74.28%
	Female	20%
	Prefer not to say.	2.86%
	Other	0.00%
	NA	2.86%
Age Range	25–34	11.42%
	35–44	60%
	45–54	5.70%
	55–64	11.40%
	65 and above	2.86%
	NA	8.62%
Education Level	High school graduate (high school diploma or equivalent, including GED)	0%
	Some college but no degree	0%
	Associate's degree in college (2 years)	0%
	Bachelor's degree in college (4 years)	22.85%
	Master's degree	42.85%
	Doctoral degree	14.28%
	Professional degree (JD, MD)	11.42%
	NA	8.60%
Areas of Expertise	Cardiovascular diseases (heart and blood vessel diseases)	34.28%
	Gait disorders (walking and balance problems)	22.58%
	Neurological disorders (nervous system diseases)	31.42%
	Pulmonary diseases (lung diseases)	20%
	Body biofluids and microfluidics (e.g., blood, sweat, saliva, and tears)	34.28%

2) Which human body parts do you associate with sensing heart rate in terms of accuracy?
3) Which human body parts do you associate with sensing heart rate in terms of simplicity?

Moreover, to give the participants more flexibility, they can choose the correct answer among nine main body parts (head, neck, shoulder, armpit, back, chest, abdomen, upper limb, and lower limb), or they can give a more specific answer based on their expertise.

3. Results

Thirty-five respondents were included in the descriptive and statistical analysis. The target sample size was based on common practice in expert elicitation studies, which typically range from 10 to 50 participants, depending on topic scope and domain access. Participants were selected from diverse fields, including biomedical engineering, clinical medicine, human factors, and digital health, to capture multidisciplinary insight. While this diversity was intentional, individual priorities may have varied by background. Basic demographic information (e.g., field, years of experience) was collected to contextualize the responses. About half of the respondents (48%) worked in engineering-related fields, and 52% worked in medical-related fields, demonstrating the importance of collaboration between engineers and medical professionals in developing medical wearable sensors. The focus of this study was to gather structured expert insight rather than conduct statistical inference, given the relatively small, domain-specific sample size and the exploratory nature of the work.

3.1. Wearable sensors for heart and blood vessel disease monitoring

Figures 2–4 present the human body parts associated with sensing heart rate in terms of comfort, accuracy, and simplicity, respectively.

Figure 2
Human body parts are associated with sensing heart rate in terms of comfort

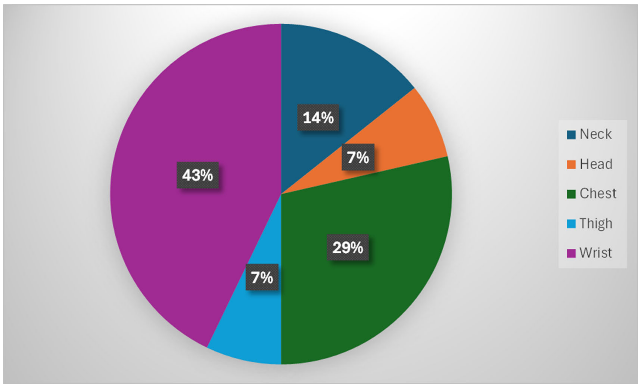


Figure 3
Human body parts are associated with sensing heart rate in terms of accuracy

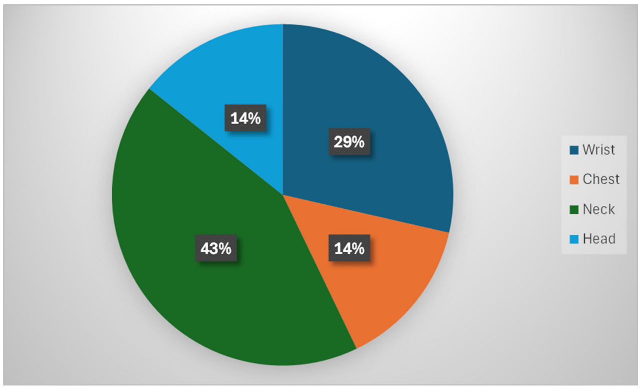
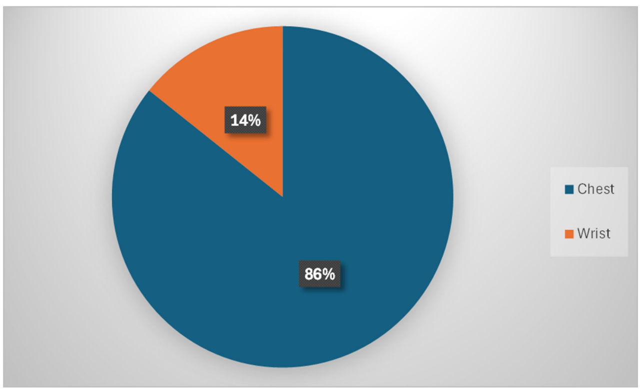


Figure 4
Human body parts are associated with sensing heart rate in terms of simplicity



Figures 5–7 present the Human body parts associated with sensing blood pressure in terms of comfort, accuracy, and simplicity, respectively.

Figure 5
Human body parts associated with sensing blood pressure in terms of comfort

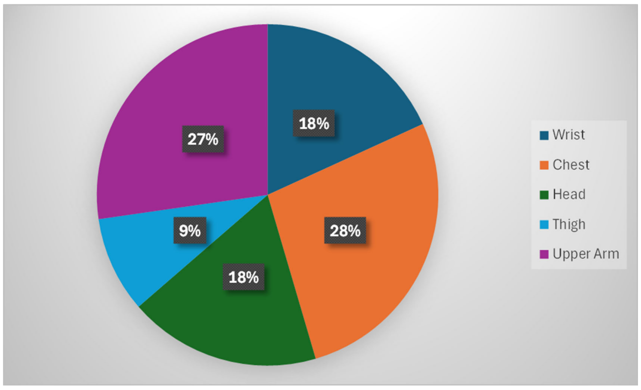


Figure 6
Human body parts associated with sensing pressure in terms of accuracy

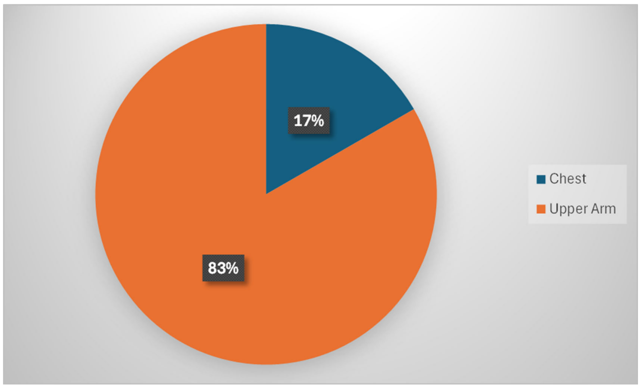
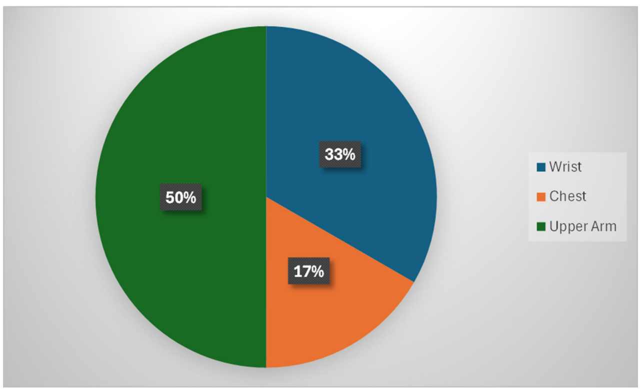


Figure 7
Human body parts are associated with sensing blood pressure in terms of simplicity



Figures 8–10 present the Human body parts associated with sensing blood oxygen level in terms of comfort, accuracy, and simplicity, respectively.

Figure 8
Human body parts are associated with sensing blood oxygen level in terms of comfort

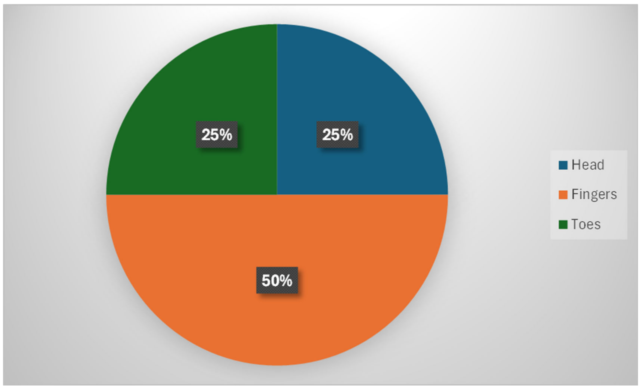


Figure 9
Human body parts are associated with sensing blood oxygen level in terms of accuracy

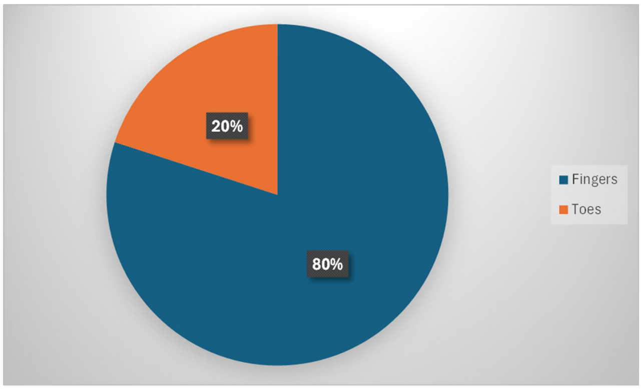
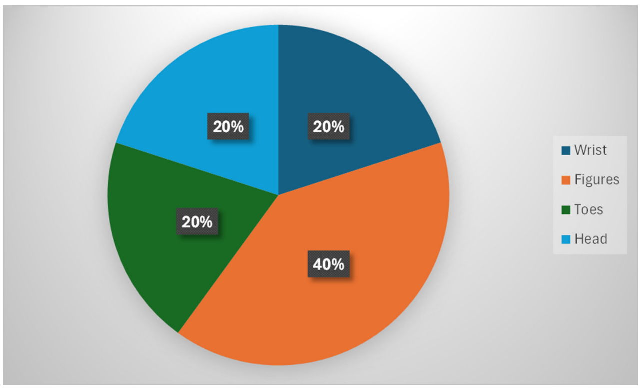


Figure 10
Human body parts associated with sensing blood oxygen level in terms of simplicity



3.2. Wearable sensors for neurological disorders

Figures 11–13 present the Human body parts associated with neuromuscular activities in terms of comfort, accuracy, and simplicity, respectively.

Figure 11
Human body parts associated with sensing neuromuscular activities in terms of comfort

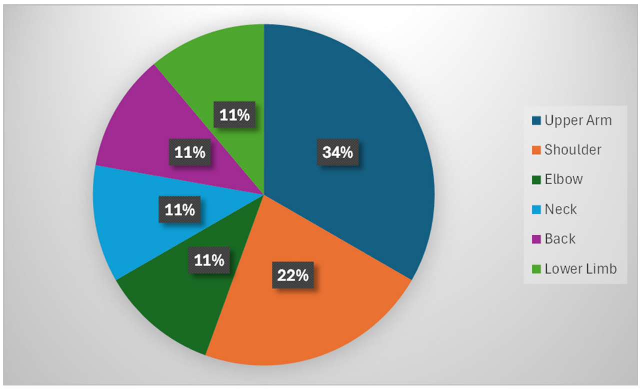


Figure 12
Human body parts associated with sensing neuromuscular activities in terms of accuracy

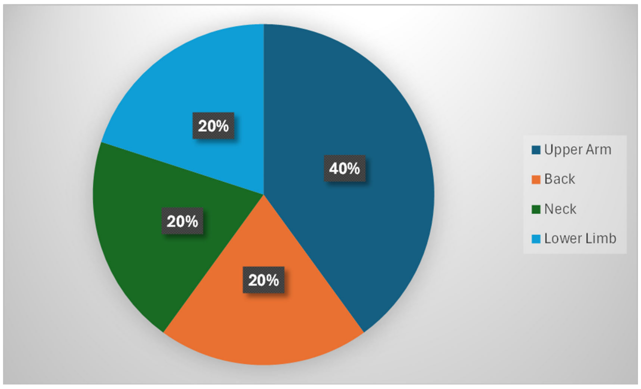
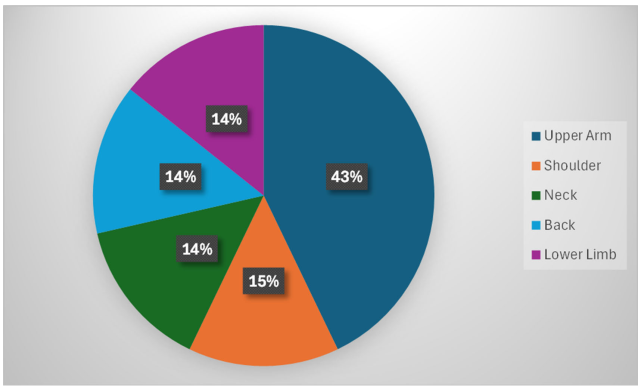


Figure 13
Human body parts are associated with sensing neuromuscular activities in terms of simplicity



Figures 14–16 present the Human body parts associated with neuromuscular activities in terms of comfort, accuracy, and simplicity, respectively.

Figure 14
Human body parts are associated with sensing seizure disorder in terms of comfort

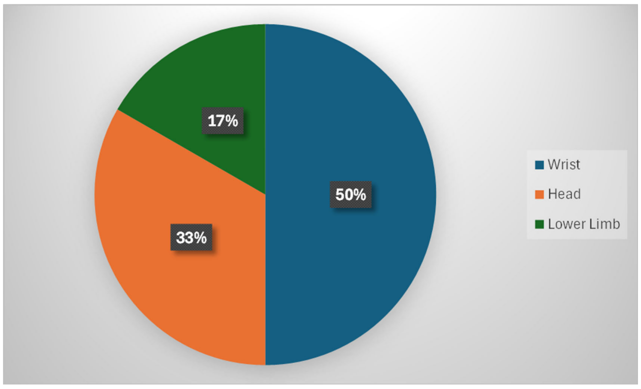


Figure 15
Human body parts associated with sensing seizure disorder in terms of accuracy

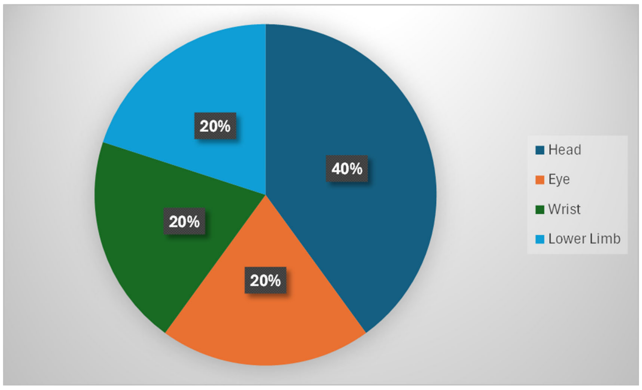
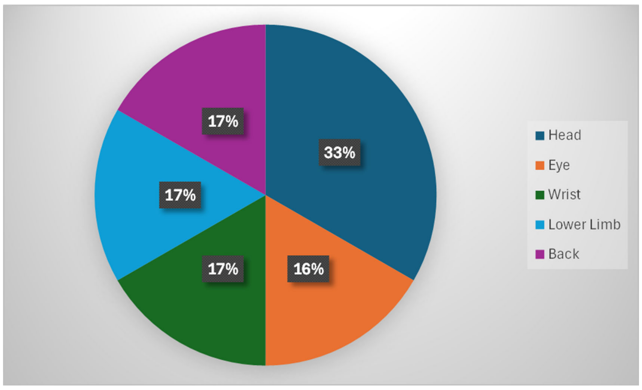


Figure 16
Human body parts associated with sensing seizure disorder in terms of simplicity



3.3. Body biofluids and microfluidics

Figures 17–20 present the Human body parts associated with continuous glucose monitoring in terms of comfort, accuracy, and simplicity, respectively.

Figure 17
Human body parts associated with continuous glucose monitoring in terms of comfort

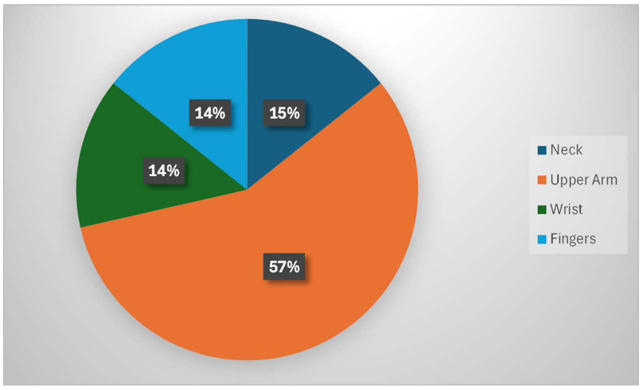


Figure 18
Human body parts associated with continuous glucose monitoring in terms of accuracy

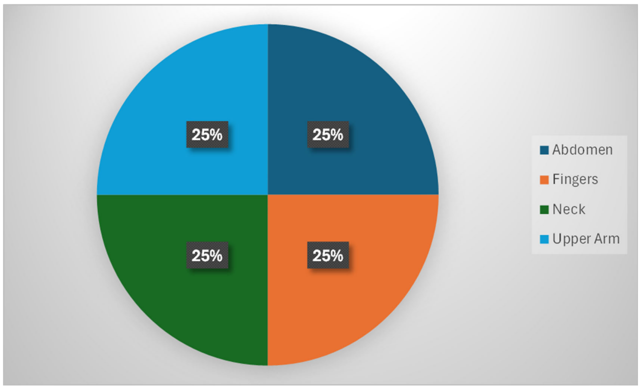


Figure 19
Human body parts associated with continuous glucose monitoring in terms of simplicity

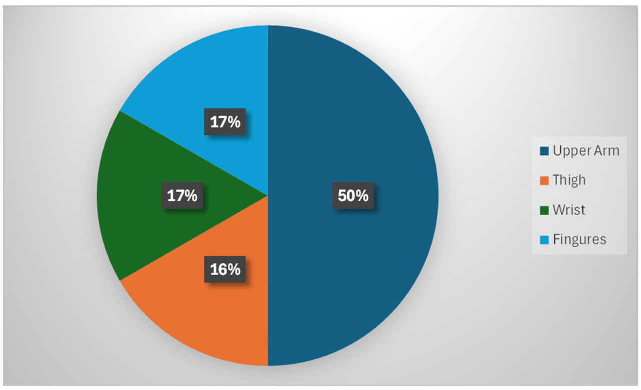
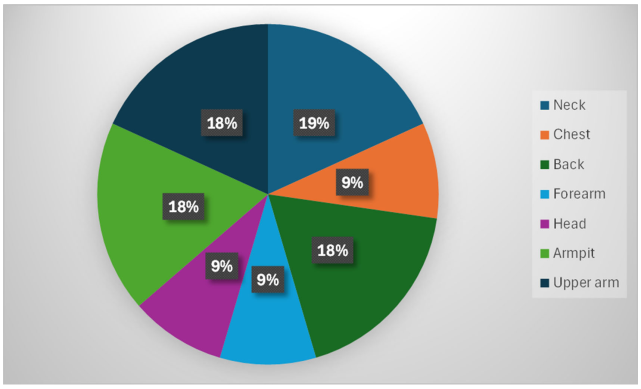


Figure 20
Human body parts associated with continuous sweat monitoring in terms of comfort



Figures 20–22 present the Human body parts associated with continuous sweat monitoring in terms of comfort, accuracy, and simplicity, respectively.

Figure 21
Human body parts associated with continuous sweat monitoring in terms of accuracy

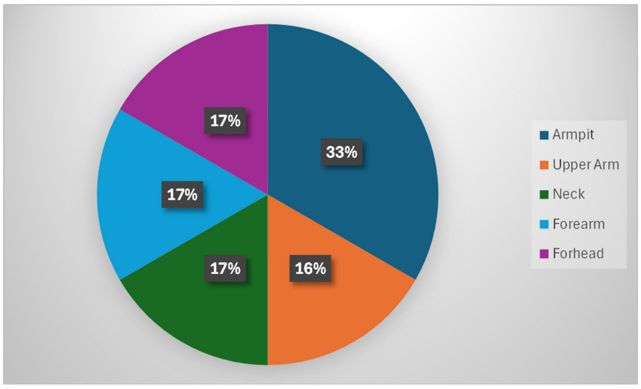
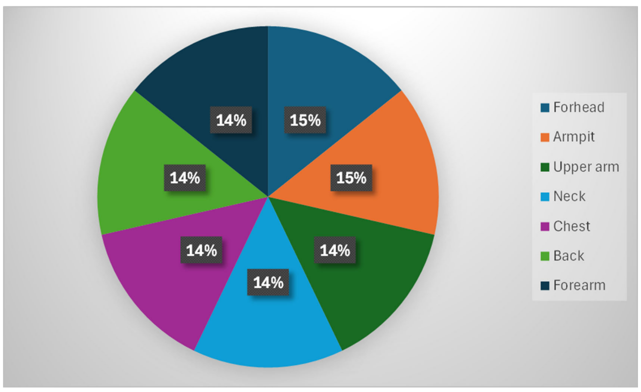


Figure 22
Human body parts associated with continuous sweat monitoring in terms of simplicity



3.4. Gait disorders (walking and balance problems)

Figures 22–25 present the Human body parts associated with human motion monitoring in terms of comfort, accuracy, and simplicity, respectively.

Figure 23
Human body parts associated with human motion monitoring in terms of comfort

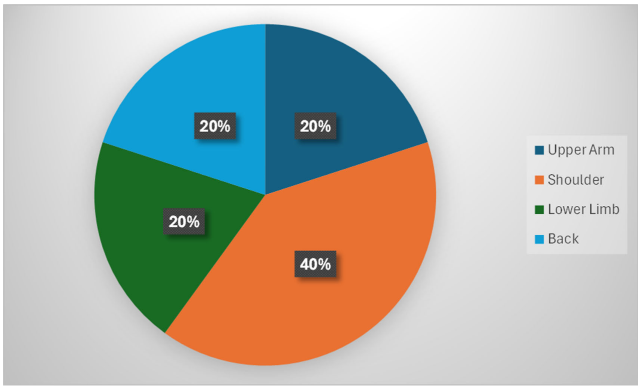


Figure 24
Human body parts associated with human motion monitoring in terms of accuracy

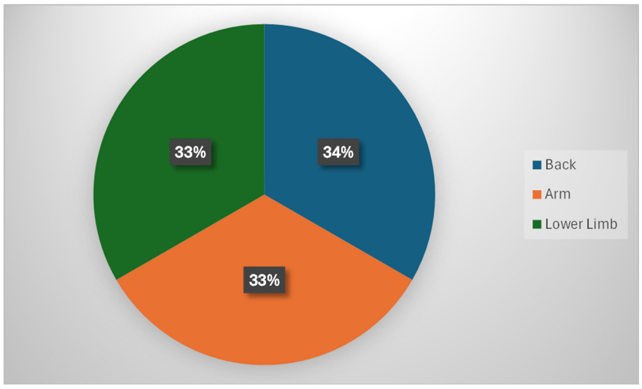
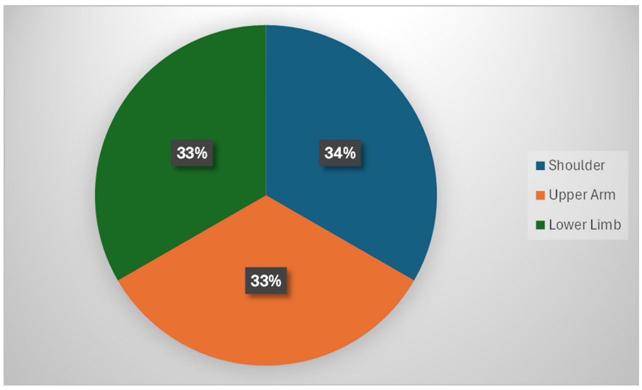


Figure 25
Human body parts associated with human motion monitoring in terms of simplicity



4. Discussion

This paper aimed to determine the best location to place wearables to continuously monitor a person's health. Based on the consumer market, it was hypothesized that the best placement would be the wrist for various tasks. In most cases, this did not match expert opinion for cardiovascular, neurological, biofluid, or gait measures.

4.1. Cardiovascular measures

Regarding heart rate monitoring, it is clear from the experts' opinions that experts prefer wrist as body part for heart rate sensors placement, for comfort; such opinion is driven mainly due to the commercially available and the well-established smartwatches in the market that are primarily using photoplethysmography (PPG) as a noninvasive simple optical method to measure heart rate such as Samsung Gear Sport smartwatch, compared to the traditional accurate, and invasive electrocardiogram (ECG) monitoring technologies, which is not suitable for home-based or long-term monitoring [8], and this is true because many people wearing watches for everyday use and accepted watches as a part of their lifestyles and outfits and measuring heart rate using watches will not disturb their everyday life activities or require them to wear an additional tool that could make them feel uncomfortable. However, recent studies suggested that using PPG sensors for monitoring heart rate can give higher-quality and more accurate results if the sensors are placed on the fingertip or earlobe [9], while the wrist is not an ideal body placement for measuring to get accurate heart rate results, as the PPG signals are susceptible to motion artifacts (MA) noise attributable to hand movements and can lead to poor or even invalid health results [10, 11]. On the other hand, recent studies indicated that the heart rate results for most of the commercially available wrist-worn heart rate sensors, such as Apple Watch, Microsoft Band, Basis Peak, ePulse2, and Fitbit Surge, could report heart rate values with acceptable error under different individuals and normal activities [12].

From an information-theoretic perspective, the variability in signal quality across different sensor placements can be interpreted through the lens of Shannon entropy, which quantifies the degree of uncertainty or disorder in a signal. While convenient, placement such as the wrist and neck often exhibits higher entropy due to MA, muscle contractions, and environmental exposure, factors that introduce greater unpredictability in signal fidelity. In contrast, more stable locations like the chest or upper arm typically generate lower-entropy signals, offering enhanced consistency for physiological monitoring. Although not explicitly calculated in this study, this entropy-based framework provides a valuable theoretical foundation for understanding placement suitability. Future work could incorporate entropy metrics directly into placement evaluation models, aligning physical design with both signal stability and human-centered constraints [13, 14]. Although many sensor systems traditionally assume Gaussian noise in modeling error distributions, recent studies have shown that wearable sensor signals, particularly those affected by MA and physiological variability, often exhibit non-Gaussian characteristics, including heavy-tailed or skewed distributions. These deviations can lead to an underestimation of uncertainty in placement-related signal degradation. Future efforts should consider more robust frameworks [10].

Moreover, although the chest is not the preferred place in terms of comfort and accuracy, the result indicated that the chest is the most accurate place to measure heart rate has been approved by many studies in the literature as the chest is usually associated with the most accurate ECG technology [15]; other studies indicated that wrist-worn heart rate wearables will unlikely replace the gold standard ECG in a severe medical problem anytime soon, as the accuracy is more concerned with tachycardia condition, and the reading can be misleading and potentially life-threatening [16]. On the other hand, surprisingly, the neck has been selected as the best place to measure heart rate in terms of simplicity; such a result could be attributed to the old and simple method of estimating heart rate using the carotid artery in the neck. In addition, we can see a few researchers in the literature trying to take advantage of the neck by using a novel wearable device to extract and identify the characteristic heart sounds and, therefore, determine the heart rate from the acoustic recordings.

The expert's answers regarding the placement of blood pressure sensors highlight the conflict between comfortability and accuracy, as the traditional and well-established invasive blood pressure measurements based on the measurement of systolic (SBP) and diastolic blood pressure (DBP) by auscultation or oscillometer based on cuff occlusion is considered uncomfortable for many patients due to the cuff inflation, in addition to the unfeasibility of continuous blood pressure monitoring due to the requirement of cuff inflation and deflation [17, 18]. Therefore, when comfort and simplicity are the main criteria, we should look for another body placement rather than the brachial artery on the upper arm. Thus, the wrist and fingers have become popular recently, which should be developed carefully, as SBP and DBP vary considerably in different parts of the arterial tree, with SBP increasing and DBP decreasing in more distal arteries [19]. However, recently, a few watch-type wearable blood pressure monitors have been validated for real-life daily monitoring. These can offer a comfortable, simple, continuous blood pressure measurement tool without sacrificing accuracy and reliability [20, 21]. However, the results indicate that while the chest is not the most comfortable place for heart rate monitoring, it could be considered a comfortable place for blood pressure sensors compared to the awkward upper arm cuff inflation traditional methods, as many recent studies discussed the potential of chest-based sensors for continuous blood pressure monitoring [22].

Measuring blood oxygen levels remotely via wearable sensors has become a trendy research topic since the COVID-19 pandemic. One of the most severe symptoms of the COVID-19 virus is a low blood oxygen level, usually below 95%. Hence, the blood oxygen level is essential for early diagnosis and infection monitoring. Moreover, monitoring the blood oxygen level is limited to COVID-19 patients. It is also crucial for patients who undergo surgery or suffer from pulmonary disorders [23]. The standard way to determine whether the oxygen level is sufficient is by measuring the oxygen saturation level within the blood, termed SpO_2 [24]. The expert's choices regarding the placement of blood oxygen level wearable sensors were fingers and toes. The most popular, noninvasive technique is a pulse oximeter that can be mounted on a fingertip, toe, or earlobe. However, the sensors must be well-mounted to get reliable and accurate measures.

This is incredibly challenging for continuous monitoring because fingers and toes are among the main moving parts of the human body [25]. Therefore, considering other human body parts for blood oxygen level monitoring has been investigated recently by many researchers. For example, Khan et al. [26] proposed a promising wrist-worn device, PPG, for measuring oxygen saturation.

Accordingly, the answers of experts revealed a gap between the latest research in wearable devices and the market for cardiovascular care, as we can see many attempts in recent research to place wearable devices among various body locations, such as ears, fingers, and feet, and using several form factors such as eyeglasses, hats, headbands, earning, bracelets, rings, sports bras, and socks [27, 28].

However, the vast majority of these devices lack any assessment regarding human factors and usability. Moreover, recent research in this field is focused on improving the accuracy of ECG and PPG signals and reducing the noise by implementing different deep learning algorithms, such as cellular neural networks [29, 30]. Any improper placement could interrupt the sensor readings or leave them susceptible to MA and background noise, which could provide unreliable and misleading data and put the user at serious health risk [31].

4.2. Neurological measures

The expert's body part choices of the placement of the neuromuscular activities sensors seem to be associated with the traditional way to measure and monitor muscle function and the related neuromuscular disorders, which is the electromyography (EMG) signal. EMG is defined as the electrical manifestation of neuromuscular activity related to a particular muscle's condition using invasive electrodes [32]. However, there are many concerns regarding the comfort, simplicity, and accuracy of these electrodes, as the difference in their dielectric properties in the presence of sweat and the erosion of the dielectric material can affect the quality of measurements in the long run. Moreover, these metal electrodes are rigid and can slip over the patient's skin, causing loss of contact. Furthermore, the electrolyte gel used could cause skin irritation and generate allergic reactions [33]. Therefore, challenges such as skin-electrode interface issues, sweat interference, and MA delay the commercialization of wearable sensors for neuromuscular activities in the market and must be addressed in the early stages of design and development [34]. At the same time, recent research efforts focus on figuring out novel ways to overcome these challenges by introducing textile-based wearable EMG sensors. For example, di Giminiani et al. [35] proposed a textile-based thigh wearable EMG sensor on the quadriceps to avoid MA. Jose et al. [36] discuss the critical role of multi-biosensor-based wireless body area networks in mental health monitoring, highlighting the need for interdisciplinary research to optimize sensor placement that links the data of ECG sensors with other biological functions such as temperature and blood pressure.

Regarding the seizure disorders wearable sensors, the vast majority of the experts agreed that the scalp is the appropriate body part to measure and monitor seizure-related health conditions in terms of accuracy and simplicity, which could be attributed to their familiarity with the traditional technique is electroencephalography (EEG) sensors, which plays significant roles in monitoring the brain activity of patients through seizures and diagnosing epilepsy [37]. However, EEG reading requires extensive analysis and interpretation experience to detect epileptic activity. Therefore, it is still unfeasible for home seizure monitoring currently using traditional EEG sensors. In addition, wearing scalp EEG for long-term monitoring is uncomfortable [38, 39]. Conversely, detecting seizure indirectly, based on movement and position recording using the commercially widely available inertial measurement unit (IMU) using accelerometers, gyroscopes, or magnetometers, can be done using wrist-worn wearable devices such as smartwatches, which can guarantee comfort criteria, as the results showed. Still, the accuracy and reliability remain questionable [40]. Furthermore, due to the unpredictability and the associated potential physical harm of seizures, many recent research studies discussed machine learning models and artificial neural network algorithms to estimate seizure risk utilizing heart rate, step count, and sleep signals, in addition to other medical records for the patient, using wearable smartwatches. They concluded that wrist-worn wearable sensors for seizure forecasting are feasible and approaching [41].

The experts' answers cannot clearly envision the optimal placement of the neuromuscular activity sensors. This can be attributed to the importance of the application of the wearable device. Hence, sensor placement varies drastically depending on the application, such as muscle activation, fatigue monitoring, or rehabilitation, in addition to the targeted muscles, as targeting specific muscles will determine the proper placement of that device. In addition, the transition of technology from clinical EMG to wearable EMG still faces many challenges regarding electrodes, the complexity and constraints of the processing, accuracy, and real-time performance [42, 43].

4.3. Body biofluid measures

Monitoring glucose levels helps with more intensive blood glucose control, specifically in patients with type 1 diabetes mellitus, alongside patients with uncontrolled hypo- or hyperglycemia [44, 45]. Choosing the proper placement for continuous glucose monitoring requires various tradeoffs between accuracy, simplicity, and comfort, as this type of sensor needs frequent calibration and integrated pumps to work efficiently [46]. Although fingers are considered the most common place for traditional glucose monitoring, the results showed that fingers cannot be a good placement choice for continuous glucose monitoring sensors in terms of comfort and simplicity, as it is painful and cumbersome [47–49]. Conversely, the upper hand and the abdomen look promising as a better placement for continuous glucose monitoring; a recent study did not find any significant difference between the accuracy of abdomen and arm continuous glucose monitoring [50]. The results also clearly showed the consensus that the abdomen is not a comfortable place for continuous glucose monitoring. However, as many experts still believe fingers are the preferred choice for glucose monitoring, this could indicate that the benefits of continuous glucose monitoring over the traditional finger-stick test are still not clear, as many diabetes patients believe the process of continuous glucose monitoring is pointless or unpleasant, so they decide to avoid it [51].

Continuous sweat monitoring has many advantages compared to other biomarkers, such as blood, saliva, and urine, as sweat is a continuously accessible biofluid and has been an unexplored source of physiologically relevant information [52–54]. Sweat has many analytes that can be linked to different health conditions, such as electrolytes (sodium ($Na+$), chloride ($Cl-$), and potassium ($K+$)), trace metals (zinc, copper, and magnesium) in addition to different organic compounds (lactate, cortisol, and ethanol), which makes the particular application of the sweat-monitoring device significant for deciding the wearable sensor characteristics [55]. The results showed that clearly, experts could not agree on a clear choice for any of the three criteria. We can see the armpit has been chosen as the most accurate place for sweat-monitoring sensors, as the armpit body the location has the highest rate of sweat generation. Compared to any other body placement, this could lead to more efficient and reliable measurements [56]. However, the armpit cannot be the appropriate choice regarding comfort and accuracy, as the continuous friction and the rapid hair growth could lead to various skin health problems, such as chafing [57]. Thus, other body placement options, such as the back and the arm, are suggested [58]. Moreover, the expert's answers regarding the proper placement of sweat sensors reveal that the technology is still immature for commercialization, as there are many critical technical challenges regarding the collection, sampling, and storage of sweat, in addition to the analytical performance issues and the required memory and power capacity of such continuous monitoring devices [59]. Addressing the previous challenges and specifying the target analytes can lead to more precise answers regarding the best placement of sweat-monitoring sensors.

4.4. Gait measures

Human gait and musculoskeletal function analysis has a wide range of applications in sports and fitness, in addition to diagnosing various age-related diseases and neurodegenerative disorders [60, 61]. Using the commercially widely available IMU, using one of the combinations of accelerometers, gyroscopes, or magnetometers, is considered the most well-established, accurate, and simplest way for human joint motion analysis [62]. Accordingly, according to the survey results, there is no preferable placement for motion analysis in terms of accuracy and simplicity, as the type of technology plays a more critical role than the placement in this criterion. Moreover, the application and the targeted joint (knee, toe, elbow, hip, ankle, neck, and shoulder) can, in many circumstances, decide on selecting the optimal sensor placement as mandatory rather than optional. However, recent developments in sensor technologies have introduced new ways for human motion analysis, such as optical fiber sensors and textile-based goniometers for angular motion monitoring of the joints [63–66]. This could provide greater flexibility in selecting the placement of the wearable sensor, and emphasize the importance of considering the human body aspects while designing and developing such devices; while creating rigid textile-based sensors can improve the accuracy of the measurements, the comfort aspect will remain questionable.

Moreover, human biomechanics exhibits nonlinear and fractal-like variability, particularly in neuromuscular activity and motion dynamics. Sensor data such as IMU signals often reflect this self-similar complexity. Therefore, considering fractal dimensioning techniques as an analytical lens for evaluating sensor placement could offer a more nuanced understanding of placement efficacy across diverse movement profiles. Future studies could explore how the fractal geometry of skin topology or signal patterns may inform optimal positioning for sustained signal stability [67].

5. Conclusions

To our knowledge, this study will be the first to study the optimal placement of medical wearables. This could open the way for a new generation of more efficient, accurate, and comfortable wearable devices that give more attention to human body parts. According to the findings, there is a gap between the latest research outcomes and the clinical use of wearables. This could be attributed to the lack of collaboration between health tech companies and medical professionals. Furthermore, engineers play an essential role in developing the sensors, hardware, and software of the wearable devices seem not to have sufficient knowledge about the anatomy of the body and the characteristics of each body part. Conversely, medical professionals are unaware of the potential capabilities and enormous opportunities that can be exploited by utilizing the latest developments in wearable technologies, which could change the ways of diagnosis, monitoring, or even treating many diseases and health conditions. Accordingly, expert medical professionals' choices regarding the placement of wearable sensors are limited most of the time to the placement of traditional sensors such as IMU, ECG, EMG, and EEG in daily clinical care, without considering the flexibility of wearable devices in terms of function and form. However, regarding wearable sensors for heart and blood vessel disease monitoring, experts' answers were more consistent with the well-established commercially available wearable devices, such as smartwatches. Accordingly, heart rate monitoring technology using ECG and PPG has not changed dramatically in the past two decades, so the importance of exploring the effect of placement of the wearables sensors among various body placements and different forms such as eyeglasses, hats, earnings, earbuds, headbands, shirts, sports bras, armbands, bracelets, wristbands, rings, and socks, taking into account the different criteria, such as the accuracy, human factors, and usability, in addition, the manufacturing aspects, is essential to understand the user's needs and improve the commercialization process, alleviate the burden on healthcare systems, and reduce the mortality rate of cardiovascular diseases through early detection. Conversely, while relating to the placements of wearable sensors for neurological gait analysis, the answers were limited to the traditional diagnosis techniques, EMG and IMU, respectively, and the application and the target muscles, joints, or nerves will play an essential role in the selection of the wearable sensor placement. Still, in the process of creating new wearable sensor materials, the human factor and usability aspects are crucial and cannot be neglected.

Furthermore, real-world deployment of wearable sensors introduces several practical challenges that extend beyond ideal placement. These include skin irritation, prolonged use discomfort, and sensor adhesion issues during physical activity or perspiration. Over time, factors like sensor degradation, battery limitations, and environmental exposure can affect signal quality, potentially leading to false positives or missed physiological events. Future research should explore wearable sensors' durability, skin compatibility, and long-term reliability across placements, especially for continuous monitoring use cases like blood pressure or arrhythmia detection.

The study's limitations are the limited number of participants, as the questionnaire only targeted the experts in medical wearables. However, even experts in a specific medical field or wearable technology might not have adequate knowledge of the other research advancements and recent technologies beyond their specialization, which highlights the urgent need for a comprehensive human-centered framework to evaluate medical wearables based on their performance criteria alongside their usability and wearability criteria, supported by long-term clinical studies, human factors assessment, and physiological data for each potential body placement. Considering AI-driven adaptive placement algorithms or data-driven techniques such as principal component analysis that consider users' lifestyles and activity levels, current and potential health risk factors, the nonlinear relation between criteria such as comfort and accuracy, and other dynamic characteristics, such as skin impedance variability, sweat accumulation, motion-induced dielectric shifts, and multi-sensor systems (e.g., EMG, ECG system), has the potential to play a critical role in optimizing sensor placement dynamically. Machine learning algorithms could integrate real-time data streams such as skin temperature, movement variability, or sweat level to adjust signal weighting or select the most reliable active sensor. In addition, a topological data analysis considers the geometrical complexity of the human body. It represents a dynamic, curved surface rather than a flat plane, offering a potential pathway for quantifying sensor-body interactions in such complex regions.

Technical factors like wireless transmission power requirements and energy efficiency are essential in wearable sensor placement. The sensor's location on the body can significantly influence wireless transmission power requirements due to variations in signal path length, tissue interference, and antenna orientation. Moreover, improving signal quality and reducing the noise-to-signal ratio by data filtration, noise reduction techniques, and adapting placement-aware data compression techniques can be beneficial. Such a comprehensive approach can fill the gap between the recent research in the field and the commercialization stage of medical wearable devices and give users a customized recommendation for medical wearable devices that fit their needs without affecting their lifestyles. Furthermore, we recognize that bringing in experts from diverse fields like engineering and medicine means there could be variation in how they interpret or prioritize different criteria. In this study version, we focused on collecting a broad range of perspectives rather than measuring statistical agreement between participants. That said, adding inter-rater reliability (e.g., Fleiss' kappa or intraclass correlation) would provide more insight into the consistency of responses, and we plan to explore that in follow-up work.

Ethical Statement

This study does not contain any studies with human or animal subjects performed by any of the authors.

Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

Data available on request from the corresponding author upon reasonable request.

Author Contribution Statement

Mohammad Y. Al-Daraghmeh: Conceptualization, Methodology, Validation, Formal analysis, Investigation, Data curation, Writing – original draft. **Richard T. Stone:** Conceptualization, Methodology, Resources, Supervision. **Fatima Z. Mgaedeh:**Writing – Review & editing.

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