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User-Centered Perspectives on the Design of Batteryless Wearables

Arwa Alsubhi[a], Reza Ghaiumy Anaraky[b], Simeon Babatunde[a], Abu Bakar[c], Thomas Cohen[d], Josiah Hester[c], Bart Knijnenburg[a], and Jacob Sorber[a]

[a]Clemson University, Clemson, SC, USA; [b]New York University, New York City, NY, USA; [c]Georgia Institute of Technology, Atlanta, GA, USA; [d]Northwestern University, Evanston, IL, USA

ABSTRACT
Batteryless wearables use energy harvested from the environment, eliminating the burden of charging or replacing batteries. This makes them convenient and environmentally friendly. However, these benefits come at a price. Batteryless wearables operate intermittently (based on energy availability), which adds complexity to their design and introduces usability limitations not present in their battery-powered counterparts. In this paper, we conduct a scenario-based study with 400 wearable users to explore how users perceive the inherent trade-offs of batteryless wearable devices. Our results reveal users' concerns, expectations, and preferences when transitioning from battery-powered to batteryless wearable use. We discuss how the findings of this study can inform the design of usable batteryless wearables.

KEYWORDS
Batteryless; wearables; designing; user study

1. Introduction

Wearables offer a wide range of applications that improve the lives of their users, from activity tracking to health monitoring and stress management. The frequent need to charge these devices hinders their intended use (Seneviratne et al., 2017), as charging interrupts some of the most critical applications to the users (e.g., activity tracking) (Motti & Caine, 2016), causing users to abandon the wearable device (Jeong et al., 2017). Additionally, batteries wear out within a few years and need to be replaced, increasing the e-waste (Hendrickson et al., 1994; Hester & Sorber, 2017b).

Using capacitors instead of batteries to store harnessed energy from the surrounding environment (light, body movements or heat) has resulted in a new generation of batteryless devices that are maintenance-free, eco-friendly, and sustainable.

However, designing such wearables is a user experience challenge due to their intermittent operation: their ability to operate is determined by the characteristics of the capacitors (which cannot hold a charge for a long period of time due to their self-discharging nature), the availability of harvested energy (which may vary substantially and unpredictably over time) and the application needs as shown in Figure 1. The ability to only operate intermittently affects many aspects of wearable design that users of existing battery-powered wearables are unfamiliar with, making batteryless devices more challenging to design. For example, while most battery-powered wearables can always respond to user input, batteryless wearables can only do so if they have captured enough energy. Moreover, batteryless wearable designers may be forced to reduce the size, type, and quality of the device's screen to compensate for the limited energy harvesting available. For example, they may have to use a small e-ink display instead of an OLED touch screen on a batteryless device. Some batteryless wearables may not be able to power a screen at all. Therefore, several tradeoffs in the design of batteryless wearables need to be considered.

Several batteryless devices have already been developed, including a mobile gaming device (De Winkel et al., 2020), a mobile phone (Talla et al., 2017), a shoe pedometer (Kalantarian & Sarrafzadeh, 2016), an opportunistic display (Dierk et al., 2018), and an interaction device for gesture recognition (Truong et al., 2018). These efforts contribute significantly to the expansion of batteryless technology and reducing environmental hazards associated with batteries (Hendrickson et al., 1994; Hester & Sorber, 2017b). However, each of these devices considers only a small subsection of the design space for batteryless wearables. The wearable design literature lacks a generalized analysis of users' preferences when considering the adoption of batteryless wearables in their daily lives.

We address this gap by investigating users' perspectives on batteryless wearable technologies for daily sensing and health tracking in various scenarios (including both indoor and outdoor) without the need for additional infrastructure equipment. Such wearables are essential for health tracking, particularly in situations where healthcare accessibility is limited. Batteryless options offer health tracking at a lower cost and require less maintenance, making them beneficial for a wider range of populations, including the elderly and children.

Although conducting the study with a real device has significant advantages, we chose to use online contextual

CONTACT Arwa Alsubhi aalsubh@clemson.edu Clemson University, Clemson, SC, USA

scenarios to reach a wider and more diverse pool of daily tracking wearable users, ensuring a broader range of perspectives, and getting more comprehensive insight into the design parameters that may affect the development of batteryless wearables. Also, this approach has been widely used in the literature to explore the user-centered design and perception of many new technologies (e.g., for smart homes (He et al., 2020; Zaidi et al., 2022), IoT health assistant systems (Faltaous et al., 2021), electric muscle stimulation (EMS) (Shahu et al., 2022), and digital contact tracing (Zakaria et al., 2022)) to help developers address design issues early in the product or prototype development cycle and better accommodate users' preferences and needs (Park & McKilligan, 2018).

We conduct a user study in which 400 users evaluate a total of 1792 different wearable usage scenarios and focus our analysis of the results on users' perceptions of the unique selling points of sensing-based batteryless wearables when compared to their battery-powered counterparts. In particular, we address the following research questions:

RQ1 What are users' common perceptions of batteryless wearables?
RQ2 What popular daily-use sensing applications do users think can be supported by batteryless wearables?
RQ3 Is there a difference between batteryless wearables and their battery-powered counterparts in which part of the body users prefer to wear them?
RQ4 How do users perceive potential data transfer methods for batteryless wearables?
RQ5 What display types—if any—do users consider most suitable for batteryless wearables?

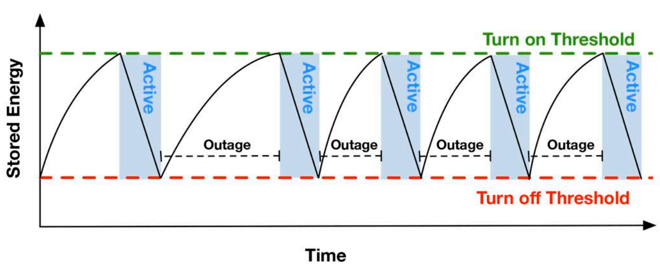


Figure 1. Batteryless devices operate intermittently with unknown periods of outages. Energy availability depends on the environmental condition and the device application.

Based on our findings, we provide actionable design recommendations that will help in balancing the trade-offs inherent in the development of usable sensing batteryless wearables in daily tracking scenarios, and that may scale to other types of batteryless wearables.

2. Background and related work

A major challenge in designing batteryless wearables is that they derive their power from environmental sources that fluctuate unpredictably and store their harvested energy in capacitors, which cannot maintain a charge for a long period compared to batteries, resulting in intermittent operation. This poses several challenges for developers and results in trade-offs for the end-users as summarized in Figure 2. In this section, we leverage existing literature to survey the prevalent design considerations for batteryless wearables.

2.1. Batteryless devices design trade-offs

2.1.1. Energy harvesting

The choice of energy harvesting depends on the intended device application, including powering a sensor/set of sensors, collecting and processing data, the intended position of the wearable on the user's body, where, when, and how often the user will wear the device, and the circumstances under which the device will be used. For instance, technologies like photovoltaic cells (Parrilla & De Wael, 2021; Song et al., 2021; Truong et al., 2018) and photodiodes depend on ambient light. Photodiodes are particularly suitable for nano power applications in miniature devices, serving both as an energy source and a sensor (Heo et al., 2018). However, the energy output of a single photodiode may not be sufficient to power sensors or more complex applications and usually requires an array of them for this purpose (Li et al., 2018). Consequently, neither of these harvesting methods is capable of providing enough energy to support sleep monitoring.

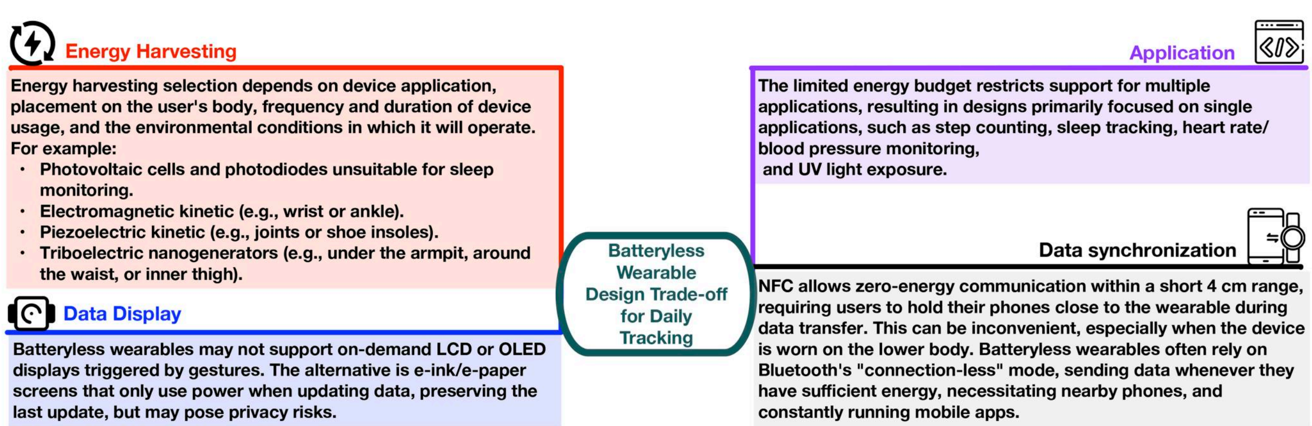


Figure 2. Key trade-offs in developing batteryless wearables.

Kinetic harvesters require substantial movement and thus cannot do so either. Among the latter types, electromagnetic kinetic harvesters require pendulum-like movements. Therefore, they will only work on a swaying wrist or ankle (Magno et al., 2016), whereas piezoelectric kinetic harvesters create power through pressure, which means that they produce enough energy when placed on joints (Tuncel et al., 2020) or in shoe insoles (Huang et al., 2018; Kalantarian & Sarrafzadeh, 2016). Triboelectric nanogenerators, another type of kinetic harvester, generate electric charges when materials come into contact and separate or rub against each other (W.-G. Kim et al., 2021; Parrilla & De Wael, 2021; Pecunia et al., 2023; Song et al., 2021). Consequently, they are most effective when strategically positioned in areas where frequent friction or contact occurs between diverse materials, such as beneath the armpit, around the waist, and along the inner thigh (Su & Kim, 2020).

Thermal harvesters extract energy from human body heat whenever there is a difference between human body temperature and the surrounding air (Parrilla & De Wael, 2021; Yan et al., 2018). The applications of this thermal harvester are limited as it might not generate sufficient energy without a significant temperature difference.

Radio frequency can be harnessed to power batteryless wearables through methods like radio frequency identification tags (RFID), power casting, or near-field communication (NFC) protocols. However, each protocol imposes some design limitations. For example, RFID requires both a radio transmitter and a reader for operation (Jaiswal et al., 2018; Jayatilaka et al., 2019; Ranganathan et al., 2018). Conversely, power casting (Stuart et al., 2021), eliminates the need for a reader but still necessitates a radio transmitter to power the batteryless wearable. Consequently, this requirement restricts the practical application of RFID and power casting to indoor environments equipped with the necessary RF infrastructure.

On the other hand, NFC capabilities are available in most current mobile phones, enabling users to transfer data or interact with batteryless wearables at no energy cost. However, NFC requires users to hold their phone within 4 cm of the wearable device and only transfers a very small amount of power. As such, NFC harvesters are suitable for interacting with batteryless wearables but not for powering them all the time. The design decision between using RFID or NFC will significantly impact the product's affordability.

2.1.2. Application

Batteryless devices operate on a tight energy budget, limiting the number of applications that can be supported since different applications require different sensors and vary in computational complexity (de Winkel et al., 2021). As a result, many batteryless wearables have been designed to support a single sensing application like step counting (Kalantarian & Sarrafzadeh, 2016), sleep tracking (Ranganathan et al., 2018), heart rate (Agezo et al., 2016), blood pressure monitoring (Cong et al., 2010), and Ultraviolet (UV) light exposure (Heo et al., 2018).

Batteryless wearables require an intuitive user interface that helps users understand the tradeoffs between enabling more applications vs. increasing their wearables' overall availability. Batteryless devices also require a new kind of user interaction paradigm that assumes inconsistent availability—if the device does not have enough power, the user will not be able to interact with the device. Thus, interactive features such as push buttons, Bluetooth communication, and touch screens that are common in battery-powered wearables may occasionally operate in their batteryless counterparts—if they have any of these features at all.

2.1.3. Data display

The display of a wearable can account for about 30% of its power consumption (Liu et al., 2017). The display power consumption depends on the screen's type and size. Most fitness trackers and smartwatches that run on batteries have a liquid crystal display (LCD) or a light-emitting diode display (OLED) that is either always on or activated when the user taps on it or performs a certain gesture. Batteryless devices may not always be able to provide this on-demand display feature due to the potential insufficiency of harvested energy under specific conditions when certain types of harvesters are used. As an alternative, batteryless wearables can use e-ink/e-paper displays (Dierk et al., 2018; Dierk et al., 2017), which only consume energy when they update the displayed information. When the device has no power, users cannot see the latest data, but at least they can see the data that was available at the most recent update since it remains on the screen until another update is made. This can, however, result in privacy concerns when the display contains sensitive information and is not turned off once the user is done interacting with the device, especially when the device is worn on a visible position.

The wearable display size affects not only power consumption but also the way users perceive the displayed information. Health information displayed on a large screen was perceived to be of higher quality than that displayed on a smartwatch's small screen (Kim, 2017).

2.1.4. Data synchronization

NFC enables zero-energy communication (Boada et al., 2019; Cho et al., 2019; Dierk et al., 2018, 2017; Escobedo et al., 2021; Heo et al., 2018; Lazaro et al., 2019). It only supports a limited range of about 4 cm, though, so it requires the users to hold their phone near the wearable until the data transfer is completed. This could be particularly cumbersome when the device is worn on the lower part of the user's body (e.g., ankle or foot).

Battery-operated wearables usually use Bluetooth Low Energy (BLE) to send collected data to users' mobile phones upon request. This process requires establishing a connection between the wearable and users' phones—the process is quite expensive in terms of energy. Therefore, batteryless wearables tend to use the BLE's "connection-less" mode, in which the device sends the data whenever it has enough energy, not upon user request. However, this approach has a limitation which requires the users' phones to be nearby and the designated mobile application to always running in the background whenever data is being transmitted (DeBruin et al., 2015; Kalantarian & Sarrafzadeh, 2016).

Using one of these methods is not limited to transferring data from the wearable to users' phones. Developers rely on users' phones to correct inaccurate on-sensor timing as well as timestamp the data they receive from batteryless wearables. Despite developing several approaches for tracking time during short power outages (Alsubhi et al., 2020; de Winkel et al., 2020; Hester & Sorber, 2017a; Hester et al., 2016; Rahmati et al., 2012), batteryless devices are incapable of accurately keeping track of time during significantly long power outages. In addition, batteryless devices do not have a 24-hour clock and cannot detect day boundaries accurately. As a result, if an application requires reasonably accurate timestamps, the users may have to carry their phones with them and collect data from their wearable with a certain frequency—which may be considered cumbersome.

2.2. Research gap: What are users' preferences regarding batteryless wearables for daily tracking?

While batteryless technology has started to expand from the Internet-of-Things to wearable devices, research on batteryless wearables (e.g., insole pedometers (Huang et al., 2018; Kalantarian & Sarrafzadeh, 2016), wrist gesture recognition wearables (Truong et al., 2018), wearables monitoring PH level (Boada et al., 2019), and smart bandages for wound monitoring (Escobedo et al., 2021)) has mostly been limited to testing devices in controlled environments rather than involving users in the development process or testing the usability of such devices in users' daily lives to determine what trade-offs users experience.

One study explored the possibility of batteryless interaction with smart objects using an e-ink display at a fingertip, combined with an accelerometer (Dierk et al., 2017). The smart objects are equipped with a vibrating motor and a wireless charger. In response to the touch, the wireless charger powers both the e-ink display and the accelerometer that detects vibration patterns of the object and updates the display at the fingertip with info about the touched object. Therefore, each object should have a unique vibration pattern to make it stand out from others. The authors tested the system's efficacy with users, but did not explicitly examine how useful such an interaction could be for the users in their daily lives.

(Jayatilaka et al., 2019) conducted a user study in a local hospital setting, studying older patients' perceptions of batteryless sensor devices that were placed over their clothes to monitor their activities. This study was carried out in a controlled setting where the batteryless wearables were powered using the radio frequency emitted from radio readers set around the patient. Before using the device, the patients were concerned about its bulkiness and performance, but after placing the device on themselves, their confidence and trust in using batteryless technology increased. The system tested in this study is RFID based has very little downtime, not causing performance perception issues.

Dierk et al. studied the usability of batteryless wearables with e-ink displays embedded in clothes (e.g., hats, shoes, and T-shirts) that can be updated with any information (e.g., counted steps) or graphical design by holding a phone close to the display (Dierk et al., 2018). Based on their findings, users found batteryless e-ink displays beneficial since they did not have to charge the device. Additionally, users liked the device's pull notifications feature and pointed out that it is less overwhelming than push notifications. Again, the device's usability was tested in a controlled setting, where the researchers could not explicitly examine how useful the device could be in users' daily lives.

The developers of Energybugs (Ryokai et al., 2014) tested a tangible approach to teaching elementary school kids about harvested energy, using a bug that lights up an LED when two types of kinetic harvesters collected enough power from the children's movements. The study found that this functionality motivated the kids to engage in physical activities and that they were connected emotionally with the generated energy.

The described studies take important steps in testing the efficacy of batteryless wearables with real users in controlled environments. However, these studies provide users with the *finished product* and seek their opinion about it. In user-centered design, developers should involve users in *all stages of the development* of digital products—including in the early stages of requirements engineering (Myers, 1994). In this study, we attempt to fill this gap and seek out users' perspectives on the design trade-offs that must be made when batteryless wearables are deployed in real-world settings. To this end, we present a scenario-based study that investigates users' perspectives regarding the set of design constraints that is common among the entire *class* of batteryless wearable sensing technologies. The results of this study will inform the design of a wide array of products and prototypes in this nascent domain of technological innovation.

3. Experimental design

To understand how wearable users perceive the trade-offs involved in adopting batteryless technology, we recruited 400 wearable-using participants and divided them equally into two groups. The first group was not informed about batteryless devices, while the second group completed a pre-survey tutorial explaining the pros and cons of this new technology. We exposed each participant (in both groups) to 12 scenarios from a total 1792 ones, each describing wearable device functionality. In the following subsections, we describe the scenarios that cover various possible future technologies and how they are distributed among participants. Additionally, we explain the pre-survey tutorial and survey questions that were utilized to assess each scenario presented and the demographics of our participants.

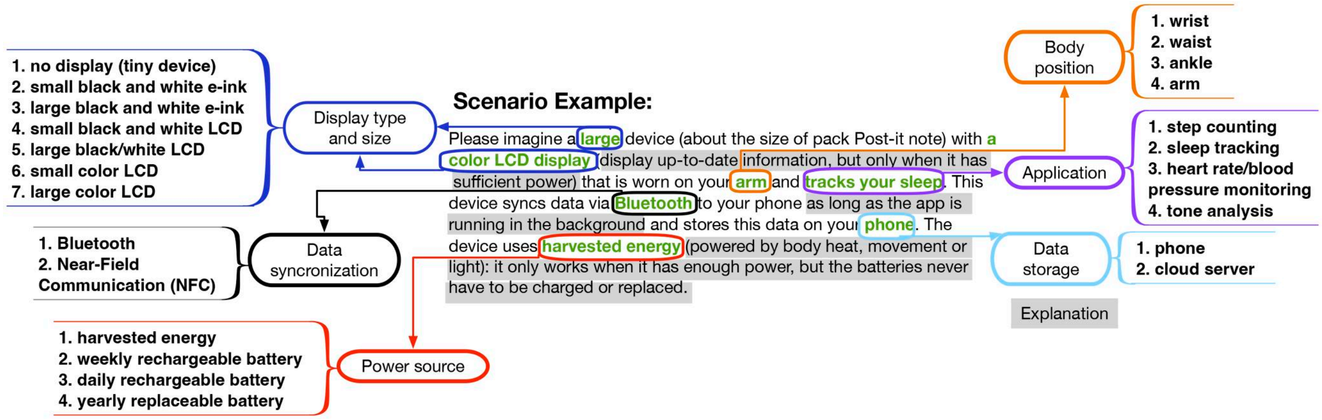


Figure 3. A sample scenario of a total 4(power source) × 4(application) × 4(body position) × 7(display) × 2(data synchronization) × 2(data storage) ≪>= 1792 unique scenarios resulting from a full factorial combination of the six scenario parameters levels that annotated in the graph. The explanation is used to highlight the pros and cons of using batteryless technology in the relevant scenario.

3.1. Scenario parameters

We measure the effect of six design parameters on how participants respond to the presented wearable. These parameters, annotated in Figure 3, were selected after carefully reviewing the existing literature describing the design challenges of batteryless wearables (discussed in section 2.1).

3.1.1. Power source

The battery life of wearables negatively impacts users' wearing behavior (Jeong et al., 2017). Our study measures batteryless wearable perception (where there is no need for battery charging or replacement) by comparing it with three types of battery charging/replacing devices that require different levels of charging/replacing frequency that are similar to commercial devices. Each scenario describes a wearable that is powered by one of four methods. Two methods involve a rechargeable battery—one that requires charging every week (e.g., a Fitbit) and another that needs charging daily (e.g., an Apple Watch). The third method involves a replaceable battery that requires replacement once every year (like the Kronaby Apex smartwatch), while the fourth method uses harvested energy (powered by body heat, movement, or light). Scenarios including the last method, explicitly mention that the device only works when it has enough power, but that the batteries never have to be charged or replaced. Effectively, this highlights the pros and cons of using batteryless technology in the relevant scenarios.

We do not differentiate between harvester types (as this is typically not something end-users concern themselves with), but we do manipulate device aspects that may be constrained by harvester types, e.g. device size and body position. Evaluating users' perceptions independent of harvesting technology makes our results robust against future technological improvements while still allowing us to compare users' perceptions against current constraints.

The power source is our main parameter of interest, allowing us to compare batteryless wearables' anticipated usability, usefulness, etc., against their battery-powered counterparts. The remaining parameters (described below) are included to test for statistical moderation effects. They can be used to determine if, e.g., users' preferred application (or body position, display type and size, data synchronization or storage method) *differs* between batteryless wearables and battery-powered wearables.

3.1.2. Application

Each scenario considers one of four major wearable device sensing applications: step counting, sleep tracking, heart rate and blood pressure monitoring, and tone analysis–used by Amazon's novel "Halo" wearable, which claims to provide users insights into their overall mental and emotional state (Aboutamazon, 2020), and this application could be implemented in a batteryless device using the self-powered microphone (Arora et al., 2018). These applications have a health-related purpose and are available on at least one device currently sold to consumers, as well as a research prototype we discussed in section 2.1.2.

3.1.3. Body Position

As we discussed in section 2.1.1, one of the challenges in batteryless wearable design is that each harvester is efficient when worn on certain parts of the body. Our scenarios consider four common body positions: wrist, waist, ankle, and arm, which have been studied in the literature for effectively harvesting energy using various harvesters for sensing-based applications (Cai & Liao, 2021; Chong et al., 2019; Halim et al., 2018; Zeagler, 2017).

3.1.4. Display type and size

The size and type of screen significantly impact the user experience of a wearable device as well as the wearable size, as discussed in section 2.1.3. In our scenarios, we contrast energy harvesting devices with battery-powered ones when LCDs or e-ink displays are used. Specifically, when the device is powered by harvested energy, we stated that LCD displays up-to-date information only when it has enough power otherwise, it is completely off, while the e-ink is permanently on but updates information only when there is enough power. For the LCD display, we consider both a black and white option and a color option (the latter generally requires more power). Since the commonly used e-ink displays are only in black and white, we do not include a color option for this type of screen. For most wearables, the screen is a major determinant of the size of the device; hence we describe the device with no display as "tiny", while the devices with a display come in either "small" (similar to the Apple watch) or "large" (similar to the LOKMAT APPLLP MAX watch). We describe the device size in each scenario as "about the size of a penny" (tiny), "about the size of an Oreo cookie" (small) or "about the size of a pack of Post-it notes" (large).

In our study, we do not analyze the power consumption of each display type and size, nor link it to what harvesters must be used to meet that consumption while keeping the device size and weight in an acceptable range. We assume that the developers will use a suitable harvester to match the display size and type consumption without making the device more bulkier. For example, a transparent solar panel could be layered over the screen as used in the commercially battery-powered LunaR smartwatch (Kickstarter, 2018). Moreover, while some combinations of parameters may be unrealistic with existing technology, we keep these in our study to maintain the orthogonal nature of our manipulations and to make our results relevant to potential future improvements in energy harvesting technology that would make a wider range of device configurations possible.

3.1.5. Data synchronization

Section 2.1.4 outlines the benefits and downsides of communication with wearables via Bluetooth versus NFC. This parameter is also evaluated in our scenarios, as each device is described to use one of these two methods. The requirements for synchronization (i.e., for NFC, the phone needs to be held near the device, while for Bluetooth, the phone always needs to be ready to receive data (the application is required to run continuously in the background) if the device uses harvested energy since the communication will be without a handshake) are mentioned in the scenario as well.

3.1.6. Data storage

Most existing wearables try to reduce energy consumption (on both the wearable and the user's phone) by moving heavy computation (e.g., sophisticated machine learning) to external servers. As batteryless devices operate intermittently, they rely more on cloud computing than their battery-powered counterparts to conserve their limited resources while still providing useful functionality to users. The transfer and storage of the collected data on an external server may present a privacy risk (Paul & Irvine, 2014), though, since this data could potentially be used to derive other sensitive information about the user, especially when this information is related to the user's health. Cloud-based processing also requires a continuous internet connection, which creates additional risks. Data interception and surveillance are increased by constant connectivity. Additionally, wearables' functionality may be limited when internet connections are unreliable, particularly in situations requiring real-time data processing, which may negatively affect the user experience.

In contrast, storing and processing data locally on a user's phone presents a different risk profile. Although it offers more control over data privacy and reduces reliance on an active internet connection, it may strain the user's device, potentially draining the battery or consuming valuable storage space in case of heavy computation processing. Moreover, if the user's phone is lost or compromised, stored data could be lost or at risk of privacy invasion.

3.2. Pre-survey tutorial Description

We created a tutorial to explain the impact of the environment on the operation of batteryless wearables. It starts by asking participants to imagine being introduced to a new technology called" batteryless" while shopping for a wearable device. This technology uses harvested energy from the surrounding environment, such as indoor/outdoor solar energy, thermal energy from the temperature difference between the surroundings and the wearer's body, and kinetic energy from the user's movements. The tutorial explains that this energy is stored in capacitors instead of batteries and presents the advantages and disadvantages of capacitors, including their smaller size and environmental friendliness and limited charge-holding capacity due to fast self-discharge, unlike batteries.

Additionally, the tutorial outlines the drawbacks of batteryless wearables, which are affected by their environment and operate in different modes depending on energy availability. For instance, they operate continuously like conventional battery-powered devices when energy is abundant. However, when energy is scarce, such as when a solar-powered wearable is partially shaded, the devices may run intermittently and experience power outages. These outages can be brief, lasting only milliseconds and going unnoticed, but longer outages can cause slower device responses or less accurate data. The device may not function in extremely low-energy environments until moving to a more energy-rich environment. The tutorial also points out that using larger or multiple harvesters can reduce power outages, although this may increase the size and weight of the device.

3.3. Scenario Description

We generate a total of 4 (power source) $\times$ 4 (application) $\times$ 4 (body position) $\times$ 7 (display) $\times$ 2 (data synchronization) $\times$ 2 (data storage) $\ll>=$ 1792 unique scenarios resulting from a full factorial combination of the six scenario parameters variations. Each resulting scenario asks the participant to imagine a wearable device based on the selected combination of design parameters according to the following template: "Please imagine a [size] device with a [type of display] that is worn on your [body position] and tracks your [application]. This device syncs data via [data synchronization] to your phone and stores this data on [data storage]. The device uses [power + explanation]." Each parameter value is highlighted in the scenario to make it easy to identify. An example scenario is shown in Figure 3. We avoided the most unrealistic scenarios (e.g. a tiny device with a giant LCD display) by carefully selecting parameters that would go together well. None of the resulting scenarios are unrealistic or conceptually impossible; some may be infeasible with existing technology, but that should not be a limitation for a user acceptance study (i.e., researchers can test the user acceptance of technologies yet to be developed).

3.4. Scenario evaluation questions

We measure the effect of the scenario parameters on participants' perceptions of the wearable device by asking them to respond to a set of questions for each scenario. Table A1 in Appendix A summarizes all dependent variables and their measured scales. First, participants are asked how much they would pay for the presented wearable device (in US dollars). Next, they are asked to rate the presented device in terms of usefulness, convenience, expected performance, perceived effort and attention, eco-friendliness, and the potential privacy concerns associated with using the device. These questions are answered on a 7-point scale ranging from, e.g., "completely useless" to "very useful."

Subsequently, participants are asked how much effort and attention they believe the presented device requires to use (the latter question is answered on a 5-point scale ranging from "virtually none" to "a lot"). To understand how the participants assess the main application accuracy of the presented wearable compared to other devices, we ask them whether they believe the presented wearable is: i) less accurate than most other wearables, ii) on par with other wearables, or iii) more accurate than most other wearables since there is no standard measurement of the wearable's application accuracy (Bassett et al., 2017).

Next, we ask participants how often they would upgrade a device like the one described in the scenario. The options include: i) about once every year, ii) about once every two years, iii) about once every three years, iv) about once every 4–5 years, v) about once every 6–10 years, and vi) I'd plan to keep this device for more than a decade. Finally, we ask participants to list the main drawback and the key selling point of the presented wearable—these are open-ended questions where participants can write anything they like.

3.5. Participants

We recruited 400 participants for our survey using the Prolific online recruitment platform[1]. Participation was restricted to participants with a high reputation (>94 Prolific score) who own a smartwatch or activity tracker. Our study included 240 participants who identified as women and 160 who identified as men, aged 18 to 72 years old. Among them, 118 were students, 158 were employed, 15 were unemployed, and 109 others. The participants were based in eighteen different countries: United States (258), Mexico (32), Canada (24), Portugal (22), South Africa (16), United Kingdom (12), Chile (7), Australia (6), Poland (5), France (2), Greece (3), New Zealand (2), Spain (2), Austria (1), Italy (2), Sweden (1), Hungary (1), and South Africa (4).

We evenly split the participants into two groups (200 participants each). The first group received no education about batteryless devices, while the second group underwent a pre-survey tutorial and knowledge test regarding the tutorial's contents before proceeding to the scenarios. In the event of failure on the knowledge test, the participants were shown the descriptive text of the tutorial and retested. This process was repeated until the participants passed the knowledge test to ensure that they paid attention to the detailed information presented to them about batteryless wearables.

Study participants had to consent to take part in the study, and once consent was obtained, the study began and took about 30 minutes to complete, after which participants were paid $4 for successful completion of the study. We removed any participant who completed the study in less than 15 minutes or did not provide valid answers to the general questions at the end of the study(only one excluded participant who was not part of the total count of 400 participants, as our recruitment efforts yielded over 400 participants in total). We provided each participant with 12 scenarios that were selected from 1792 scenarios using a fractional factorial design that balances both within- and between-subject assignment of each parameter's main effects, ensuring that all participants are equally exposed to both within- and between-subject variations (i.e., avoiding similar scenarios and ensuring that each participant is exposed to one batteryless scenario). For each scenario, we asked participants to carefully read the scenario and then answer all related questions about it. After concluding the scenario evaluations, participants answered a number of general questions, including demographics.

3.6. Methodology

To show how different scenario parameters influenced participants' responses toward the presented wearable device for each scenario, we ran several linear and generalized linear mixed-effects models. As a baseline for our comparisons, we used a wearable device that requires *daily charging*, is equipped with a *small color LCD screen*, is designed to be worn on the *wrist*, has *step counting* application, syncs data via *Bluetooth*, and saves the collected data locally on the *user's phone*. We collected data from two distinct groups of participants: the group of participants who did not receive a training video, and the group of participants who did. We first divided these two groups for analysis. If we found similar results in both groups, we merged the data to obtain a comprehensive perspective. Conversely, when we observed variations in the results, we analyzed each group separately to account for these differences. This approach allowed us to carefully consider the nuanced differences and similarities within the data and ensure that our analysis accurately reflected the distinct characteristics of each group.

Table 1. Summary of the study key findings for batteryless wearables.

Batteryless wearables perceptions	• Harvested energy reduces the device's perceived effort and attention, as no charging is needed. • The lack of the pre-survey tutorial increases batteryless wearables' usefulness and performance expectations. • The pre-survey tutorial uncovered misconceptions like batteryless devices have similar charging times as battery-powered ones, and thinking certain harvesters only work outdoors, limiting indoor use. • Boosts users' perception of the device eco-friendliness. • Increases the anticipation of longer usage (>3 years) before upgrading to a new device. • Higher price expectations.
Preferable applications	• Step-counting is perceived as more useful and advantageous when the device is powered by harvested energy compared to battery. • Sleep tracking and heart rate/blood pressure monitoring are perceived as useful but less eco-friendly, as participants are more likely to believe they will require additional power sources due to energy limitations from harvesting energy. • Tone analysis is perceived as less useful, inaccurate, and eco-friendly, raising privacy concerns among users compared to other presented applications.
Preferable body placement	• Wrist-worn device is perceived as the most convenient choice compared to wearing it on the ankle, arm, or waist. • Arm-worn device is perceived as more useful and convenient when powered by harvested energy instead of batteries.
Preferable data syncing and storage	• Syncing wearable data to phones via NFC is perceived as less convenient but requires less effort than Bluetooth. • Storing data in the cloud raises privacy concerns' perception, while local storage increases the perceived risk of data loss if the phone is lost or stolen.
Preferable display type and size	• Small screens are perceived as more convenient than larger ones. • Devices without screens are perceived as more convenient and reducing perceived privacy concerns. However, participants expressed concerns about needing to check their phones for data viewing. • There is no strong preference perceived for LCD over e-ink displays but mixed feelings are noted in free-text responses regarding e-ink's perceived advantages, limitations, and misconceptions.

To test the main effects of the parameters, we used a step-wise forward approach in which one of the remaining parameters was added to the model at every step and compared to the previous model using omnibus tests to determine if the scenario parameters and their interactions significantly influence the dependent variables. Once we added all the main effects of each scenario parameter to the model, we tested the two-way interaction effects between power and other parameters one by one (comparing a model with all main effects in addition to the interaction effect under consideration against a model with only the main effects) and consider only the significant ones. Interested readers can find detailed results of the quantitative analyses in Appendix A. Differences between specific levels of statistically significant parameters are presented throughout the paper using aggregate plots with errorbars.

Additionally, we conducted a thematic analysis of the two open-ended questions responses to identify the most prevalent themes. We systematically reviewed the responses, identified recurring patterns and concepts, and selected participant quotes that best exemplified each theme. These quotes are integrated with the quantitative results to provide contextual information and illustrate the themes identified in the data. This approach provides a more comprehensive understanding of the research question and enhances the interpretation of the quantitative data.

4. Results

In this section, we organize our findings into themes that emerge from the initial research questions presented in the introduction. Hence, we highlight results from our quantitative analyses as they pertain to each theme. We complement these quantitative results with findings from a qualitative analysis of responses to the two open-ended questions that directly asked about the presented device's drawbacks and selling points. Table 1 summarizes our study findings.

4.1. Perception of batteryless wearables

We address the research question RQ1 by measuring participants' perceptions of batteryless wearables. Specifically, participants were asked to rate each scenario in terms of perceived usefulness, convenience, effort and attention, accuracy of the main application, eco-friendliness, and willingness to pay for the presented device. The power source parameter (which compares batteryless devices against alternatives that need periodic charging) had a modest but significant effect on all of these parameters. The omnibus effect of the power source (and all other parameters) can be found in the appendix. Below, we describe the difference between batteryless devices and devices that must be recharged daily (our baseline condition).

Both groups find that utilizing energy from the surroundings significantly reduces the effort and attention involved in charging and maintaining the device, compared to devices that must be recharged daily ($p < .0001$, $b = -0.335$). This benefit is also reflected in an increased perceived convenience ($p < .0001$, $b = 0.455$) of batteryless devices compared to their conventional counterparts. For instance, a participant gave the example of a watch currently available on the market that is powered by body movement and how convenient it is:

> It uses harvested energy, powered by body heat, movement, or light that should be the main selling point. People like automatic watches a part of the reason is that when people wear it long enough, it will always be running, and that's convenient.

However, individuals who did not receive the pre-survey tutorial about batteryless devices have a higher perception of their usefulness ($p < .0001$, $b = 0.330$) and higher expectation of overall performance ($p = 0.0077$, $b = 0.199$) than their battery-powered counterparts. Moreover, the participants from this group expected batteryless wearable applications to be more accurate ($p = 0.0013$, $b = 0.098$) than devices that need to be charged every day. This is surprising since the intermittent availability of harvested energy would most likely make batteryless wearables *less* accurate than their battery-powered counterparts, although we highlighted the intermittent operation in the presented scenario of the batteryless wearable by stating that it works only when it harvests enough energy. Indeed, our results suggest that user expectations about batteryless wearables may have to be corrected, as one of the participants who did not receive the tutorial stated:

> The harvested energy, if it works well. It only works when it has enough power–would that ever not happen? If that is minimized close to 0, then it's good.

These false expectations seemed to be corrected among individuals who received the tutorial; there were no statistically significant positive or negative effects on the perceived usefulness, the overall expected performance, and applications accuracy of the devices powered by harvested energy compared to their battery-powered counterparts; however, participants from this group raised concern about the reliability of the collected data and lack of system transparency as some participants pointed out:

> The drawback of such a device that its power source is not always reliable. So it could have inconsistencies in its data.

> As the device only works when it has enough power, the device may not work consistently and may not be reliable.

> It only works when it has enough power, so you never know when it has enough power.

Although the high expectation about the batteryless overall performance and application accuracy was corrected within the group who received the tutorial, new misconceptions were revealed. Specifically, participants incorrectly assumed that the charging time of batteryless devices was similar to that of battery-powered devices. Furthermore, some participants believed that certain harvesters, such as thermal and solar, only functioned in outdoor settings, which would render the devices unusable for extended periods of indoor use.

> If not worn for a long time the device will find a hard time gaining it's power for immediate use on next usage.

> It uses harvested energy, so it could run out of power if you're not moving enough or if you're out in the cold.

> It only work when it has enough body heat. So, in winter it may not work.

> It would take a lot of effort to keep it charged. I either have to continuously move or be in direct sunlight.

Powering a device from harvested energy also increases users' perception of the eco-friendliness of the device in both groups ($p < .0001$, $b = 1.515$)—power source was the strongest predictor of perceived eco-friendliness in our study. Furthermore, a wearable that is powered by harvested energy is more likely to be upgraded (replaced by a new device) after more than three years of use ($p < .0001$, $b = 0.595$) than a wearable powered by a battery that requires daily charging. This will help in reducing the negative impact of e-waste on the environment and aligns with the long lifetime of capacitors, unlike batteries which wear out within a few years.

These favorable perceptions of batteryless wearables translate into a higher price expectation in both groups, as participants who did not receive any education about batteryless devices were willing to pay a considerably higher price if their wearable was powered by harvested energy ($p < .0001$, $b = 10.90$). However, the difference was significantly smaller for those who received the tutorial ($p < .0001$, $b = 5.94$). This price expectation may become an obstacle: participants consider the high expected price of a batteryless wearable as a main barrier to owning such a device. As one participant stated:

> The main drawback of this device is price point will probably be high with the renewable technology

4.2. Possible applications for batteryless wearables

Research question RQ2 considers the usage applications that batteryless wearables could support as perceived by users knowing that the device works only when it harvests enough energy. We measured participants' perceptions of possible applications of batteryless wearables by considering the effect of the "application" parameter (and where significant, its interaction with the "power source" parameter) on the device's usefulness, privacy concern, expected accuracy, and eco-friendliness.

Figures 4(a,b) show that participants from both groups generally found the presented applications useful, except for the tone analysis ($p < .0001$, $b = -1.791$). As one of the participants wrote:

> This device is somehow useless, I don't need to know the tone of my voice

Others considered this application to only be useful for a specific group of users in particular situations, thereby not requiring them to continuously wear the device:

> People who speak too loudly that are trying to quiet their tone maybe

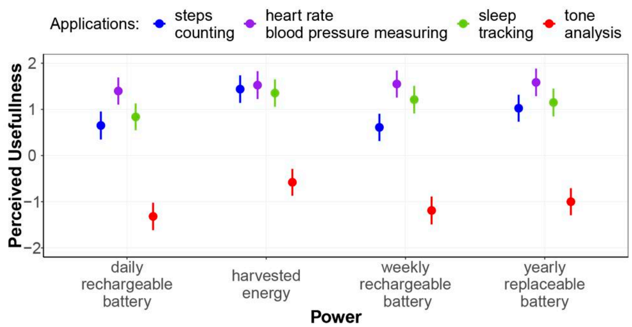
> The function does not seem very relevant to the general public (maybe useful for people who actually need to monitor their voice tone, like singers

Participants from both groups also expected tone analysis to be less accurate than the step-counting application (our baseline) regardless of the device power source($p < .0001$, $b = -0.267$), which according to the free-text responses, mostly seemed to be caused by a belief that the microphone used for the tone analysis would likely pick up other sounds and voices:

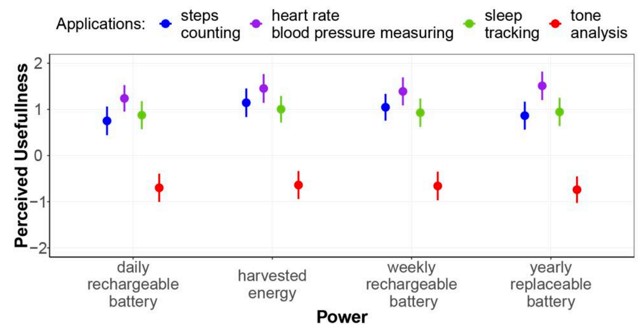
> It doesn't seem like it would be accurate, will it pick up other voices?

> The microphone may have some problems with catching the voice of a person speaking.

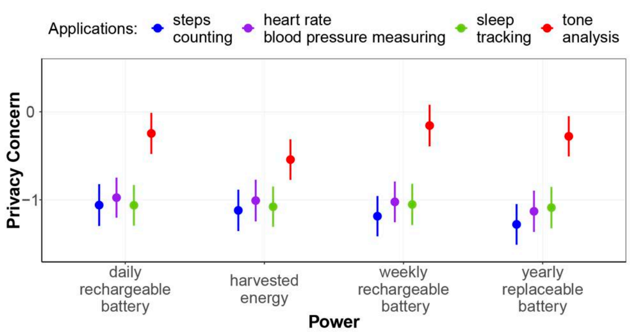
Furthermore, participants anticipate tone analysis to be less eco-friendly ($p < 0.0001$, $b = -0.181$), and the application raised significantly more privacy concerns ($p < .0001$, $b = 0.858$) among our participants in both groups(see Figure 4(c)). This result is supported by our qualitative data. For instance, one participant wrote as a main drawback of the presented device:



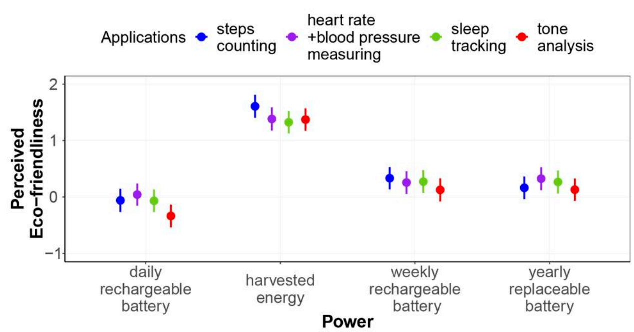
(a) The step-counting application was perceived as more useful when powered by harvested energy among those who did not receive the pre-survey tutorial.



(b) Perceived usefulness of the device's application among participants who received the pre-survey tutorial.



(c) Perceived privacy concerns of the device's application in both groups.



(d) Perceived eco-friendliness of the device's application in both groups.

Figure 4. The effect of the device's main application and its interaction with how it is powered on the perceived usefulness, privacy concerns and eco-friendliness. Tone analysis is less useful and increases the perceived privacy concern regardless of how the device is powered in both groups. All presented applications (except the step counting) are perceived as less eco-friendly when the wearable device is powered by harvested energy.

> It records personal data. It records the tone of your voice and that could be the invasion of people's privacy.

Tone analysis is the most difficult application to support with batteryless technology due to the high energy consumption requirements of this application. Even with the use of a self-powered microphone, as demonstrated in previous research (Arora et al., 2018), the application still necessitates intensive computations. However, our results suggest that this application is generally undesirable anyway—a benefit for batteryless wearables.

We found an interesting interaction effect between the power source and application on usefulness ($\chi^2(9) = 21.75216$, $p = .0097$, see Table A4 in Appendix A): as shown in Figure 4(a), the individual who did not receive education about batteryless are particularly appreciated using harvested energy to power step-counting devices—this combination leads to higher perceived usefulness than for the step-counting devices that are powered by batteries. Some participants expressed that using harvested energy to power a fitness tracker would be a motivation for being active and eco-friendly. For example, one participant explained:

> The key selling point is its harvested energy. Not only does it deem as sustainable but also encourages movement and appeals to a healthy lifestyle.

In contrast, participants are less willing to use a wearable device to count their steps if it requires a daily recharge—something they could then just as well accomplish through their phones, as one participant pointed out:

> Recharged once a day. The benefit of other wearables is that they don't have to be charged frequently. Otherwise, my phone also is charged once a day and counts my steps. I don't need this device.

In contrast, individuals who received the tutorial about batteryless don't show a strong preference for batteryless applications, but some of them express that step counting is the most appropriate one:

> Key selling points of this device are ability step counting, and never having to be charged.

> The key selling point of this device is likely to be its convenient form factor and the fact that it can be worn on the ankle, allowing for a more accurate count of steps. The use of harvested energy means that the device is always ready to use and the user never has to worry about charging it.

Finally, we found an interaction effect between the power source and application on the perceived eco-friendliness of the device ($\chi^2(9) = 21.349$, $p = 0.0112$, see Table A9 in the appendix). As shown in Figure 4(d), participants from both groups found the sleep tracking and heart rate/blood pressure monitoring applications *less* eco-friendly on a batteryless device compared to the step counting application (for battery-powered devices these applications are perceived to be roughly equally eco-friendly). Arguably, whereas in participants' intuitive understanding step counting can easily be powered by harvested energy (as walking generates ample kinetic energy and is usually performed during the day where harvesting energy from light is possible), they likely believed that sleep tracking and heart rate/blood pressure monitoring would require supplemental sources of power (as heart rate/blood pressure needs to be monitor periodically and the harvested energy might not be sufficient, as well as sleeping generates little kinetic energy and is often done in darkness), as some participants explain:

> If it's meant to be worn when you sleep, then how will it ever get its natural charge.

> It may not work when it doesn't have enough power. If you need to use movement or body heat, that could be hard under some health conditions. And if you are trying to measure your blood pressure because you are worried it is high, moving around to get the device working could be bad.

4.3. Batteryless wearable body position

Research question RQ3 considers the part of the body where users would prefer to wear batteryless wearables. We measured participants' preference for the wearable's body position by analyzing the effect of the "body position" parameter and its interaction effect with the device power on participants' perceived convenience, and the perceived usefulness, effort and attention of the presented device.

Participants in both groups expressed that wearing the wearable device on the ankle ($p < .0001$, $b = 0.457$), waist ($p < .0001$, $b = -0.460$), or arm ($p = 0.0061$, $b = -0.172$) is considered significantly less convenient than wearing it on the wrist (see Figure 5) regardless to how the wearable is powered. Wrist-worn devices seem most appropriate regardless of the application because participants are likely biased by prior exposure to wrist-worn wearables (e.g., most commercial wearable devices are wrist-worn).

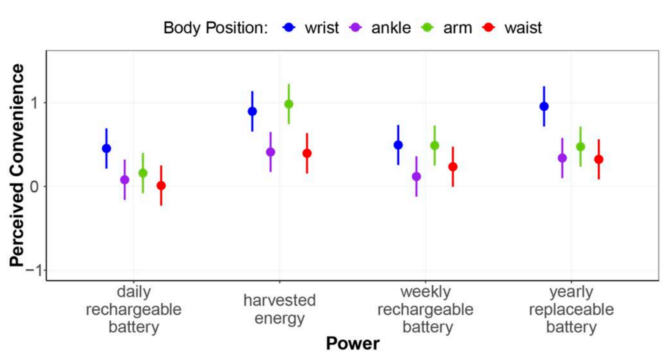


Figure 5. The interaction effect between the device's main power source and where it is worn on the perceived convenience in both groups. Wrist-worn devices are more convenient than other devices worn on other body positions. Arm-worn becomes more convenient when it is powered by harvested energy compared to when it operates with a battery.

However, we found an interaction effect between the device body placement and its power source ($\chi^2(9) = 22.43866$, $p = 0.0076$, see Table A6 in the appendix), showing that arm-worn device perceived more convenient when it is powered using harvested energy than the battery counterparts.

Furthermore, individuals who were educated about batteryless, found that arm-worn devices are more useful when powered by harvested energy compared to batteries ($\chi^2(9) = 24.14036, p = 0.007$, see Table A5 in the appendix)

4.4. Data synchronization and storage

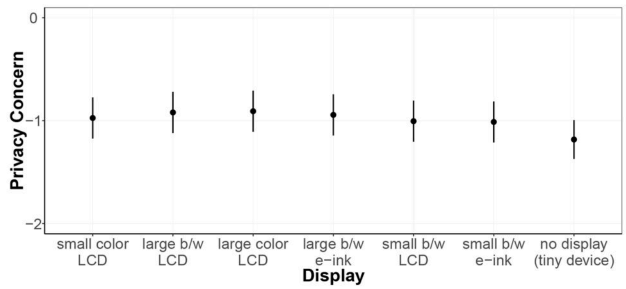
Research question RQ4 considers the most suitable method from users' perspective for batteryless wearables to transfer data to their phones, where it can be processed further and/or sent to an online data collection platform. We address this research question by testing the effect of the "data synchronization" parameter on participants' perception of the convenience of the described device, and their perception of usefulness, the effort, and attention needed in the device's daily operation. We also considered the effect of the "data storage" parameter on participants' perceived privacy concerns.

Participants in both groups perceived syncing wearable data to their phones via NFC as less convenient ($p = 0.0170$, $b = -0.096$) and required more effort and attention ($p = 0.0533$, $b = 0.0219$) compared to using Bluetooth. This is because the phone needs to be held close to the wearable device until the data transmission is completed, as we explained in the affected scenarios (where data synchronization = NFC). Moreover, some users were not familiar with this technology, despite it is increasingly used in applications like headphone pairing and mobile payment options like Apple Pay, as a participant mentioned:

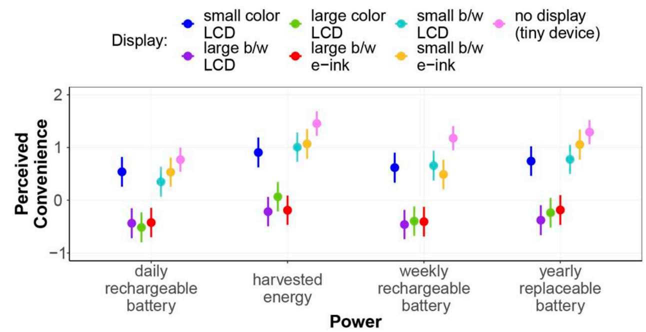
> Speaking for myself I have never used NFC on my phone. So I could say it's a bit of an inconvenient.

Participants who did receive the tutorial about batteryless found that using NFC is less useful ($p = 0.0239$, $b = -0.116$) than using Bluetooth for data synchronization, whereas individuals who did not receive the tutorial don't have any strong preference in term of usefulness.

One interesting caveat for batteryless wearables is that in order to use Bluetooth with a limited amount of power, they may not be able to complete a traditional "handshake" data transfer protocol. This means that users must perpetually leave the application that receives the data running in the background on their phones, lest the data transferred from the wearable is not properly received. We mentioned this caveat in the affected scenarios (where power = batteryless and data synchronization = Bluetooth). Consequently, there is a significant interaction effect between how the device is powered and its capability to sync the data to the user's phone on the perceived effort and attention ($\chi^2(3) = 10.41105$, $p = 0.0154$, see Table A13, showing that participants in both groups perceive using NFC when the device is powered by harvested energy less effort and attention than



(a) Perceived privacy concern of the device's screen type and size in both groups.



(b) Perceived convenience of the device's screen type and size in both groups.

Figure 6. The effect of the device's display type and size on the perceived privacy concern and convenience. Screenless devices perceived less privacy concern compared to other devices with screens. All large screens are perceived as less convenient than small ones regardless of how the device is powered.

using Bluetooth, which requires the user to ensure the receiving application is running to avoid losing data. This also, raises concerns about the phone's battery depletion and privacy violation, as some participants pointed out:

> The drawback of this device is that you would have to make sure the app is always running in the background, which may bring up privacy concerns

> App has to run in the background which drains the battery quicker.

> The app running in the background could limit its usability, as people may forget to leave the app running or may not want to sacrifice battery life on their phone.

In terms of data storage, we do find a significant effect of this parameter on privacy concerns among all participants in both groups, with cloud storage causing significantly greater concerns than local storage regardless of the wearable power source ($p < .0001$, $b = 0.317$). As a counterpoint to this concern over cloud storage, one participant mentioned that storing data locally on the phone increases the risk of data loss if the phone is lost or stolen:

> What will happen if my phone gets lost? will I be able to store the information again? That might be the main drawback. I don't know if the data is transmittable.

4.5. Display type and size

Research question RQ5 asks whether users expect batteryless wearables to have a display, and if so, what type and size of the display is most suitable in their opinion. We address this research question by measuring the effect of the "display" parameter on participants' perceived convenience and perceived privacy concerns. The display parameter acknowledges that the display is an important determinant of the overall size of a device: devices without any display can be tiny (i.e., the size of a penny), while devices with a display range from small (i.e., the size of an Oreo cookie) to large (i.e., the size of a pack of Post-it notes).

As shown in Figure 6(b) the display parameter has a significant effect on perceived convenience in both groups: wearable users found small screens more convenient than large screens, including black-and-white e-ink ($p < 0.0001$, $b = -1.0002$), black-and-white LCD ($p < 0.0001$, $b = -1.071$), and color LCD ($p < 0.0001$, $b = -0.970$). Interestingly, a device without a screen was even perceived to be more convenient than a small screen ($p < 0.0001$, $b = 0.473$). Also, another advantage of the screenless device significantly reduces the user's perceived privacy concern ($p = 0.0003$, $b = -0.208$); Figure 6(a). We suspect that participants have lower privacy concerns with screenless devices because such devices cannot display sensitive information that could potentially be read by a coincidental onlooker. Furthermore, one participant mentioned that sleep tracking devices benefit from not having a screen that could unintentionally light up in the dark:

> [I like] how small it is and that there is no display. I use my Apple Watch to track my sleep but sometimes the display lights up in the middle of the night and wakes me up.

Despite the advantages of screenless devices, the free text responses revealed that many participants expressed concerns about the need to check their phones to view the collected data. As one participant noted:

> The drawback of this device is that there is no display - you have to have your phone to see the data.

This concern is valid particularly when the user is unable to check her phone immediately due to various reasons such as social situations, busy work, or simply not having her phone nearby.

In terms of display type, we find no evidence that LCD displays are significantly preferable over e-ink displays (which require less power and are, therefore generally more suitable for batteryless devices). However, our free-text response questions show that participants do have mixed feelings about the latter. While some believe that the use of e-ink limits the wearable device, or mistakenly think that it wastes stored power (since the information is always displayed as we explained in the affected scenarios (where power = batteryless and display = e-ink), while others think it offers an advantage:

> The e-ink display might make the use cases for the device quite limited.

> Having the screen stay on seems wasteful.

> I like e-ink tech, it is the most eco-friendly possible.

Finally, we note that display type and size did not show any significant interaction effects with the device power source.

5. Discussion and design implications

We structure our discussion and design implications reflecting on the study results based on the research questions outlined in the introduction, including batteryless prescriptions, preferred sensing applications, convenient body placement, favorable data synchronization and storage options, and desired display sizes and types. At the end of this section, we emphasize the importance of educating users about the differences between batteryless devices and battery-powered counterparts to adjust their expectations and ensure a smooth transition.

5.1. Improving user perceptions of batteryless wearables

Both groups of participants in our study liked the idea of not having to charge or replace the battery of a batteryless wearable. However, those who did not receive the tutorial seemed to lack an understanding of the potential limitation: the batteryless device's intermittent operation when it fails to harvest sufficient power. On the other hand, the other group raised concerns about the reliability of data collection due to this intermittent operation. To address this concern and minimize extended power outages, the designers of batteryless wearables should consider utilizing multiple energy sources, such as ambient light, body heat, and movement, rather than relying on just one type of power source. This would allow the device to harvest energy more robustly even as the surrounding environment and user activity change while the device is in use (Magno & Boyle, 2017; Magno et al., 2016; Song et al., 2021): for instance, a kinetic harvester will not work while the user is sitting down in his/her office, but in that case, a photovoltaic cell may be able to harvest energy from indoor light. In addition, there is a decreasing rate of return on the size of any single harvester, e.g., a photovoltaic cell of twice the size does not necessarily produce twice the amount of electricity under the same light conditions. As such, several smaller harvesters of various types of energy might generate power more efficiently than a single larger one. As an example, PowerWatch (n.d.) continually charges up its battery using both thermal energy generated from body heat as well as solar energy while maintaining a small size, especially for wrist-worn devices. Arguably, solar cells can be customized to meet wearable energy, size, and weight needs. For instance, a flexible solar panel can be placed on the wearable band while other harvesters like MATRIX Prometheus (thermal harvester) (Matrix Industries, n.d.) or a microkinetic harvester (like the one produced by Kinetron (n.d.)) can be placed inside the wearable case along with flexible main circuit board to achieve the goal of multi-source powering and small size as shown in the two wrist-worn suggested designs in Figure 7.

It is important to note that, unlike battery-powered devices, batteryless wearable devices will inevitably suffer from reliability issues due to power outages of unknown length, even if they use multiple harvesters. Developers must investigate to what extent the users of batteryless wearables are willing to accept the inevitable unreliability of frequent power outages and find ways to compensate for the lower reliability (e.g. using lightweight machine learning techniques to estimate the lost data during these outages (Abedin et al., 2019; Izonin et al., 2019; Monjur & Nirjon, 2022)).

Additionally, participants have concerns over the data reliability of the batteryless device due to the uncertainty of when it loses power. While recent works have attempted to infer missing data during power failures (Abedin et al., 2019; Izonin et al., 2019; Monjur & Nirjon, 2022), providing users with insight into the data collection process could prove beneficial. We propose that developers offer users a timeline of data collection on their mobile phones, enabling them to clearly differentiate between the collected and inferred data. By having access to this timeline, users can better understand when the device was active and when data was estimated (device was inactive). This transparency empowers users to make informed decisions about the reliability of the data and gain a deeper understanding of the

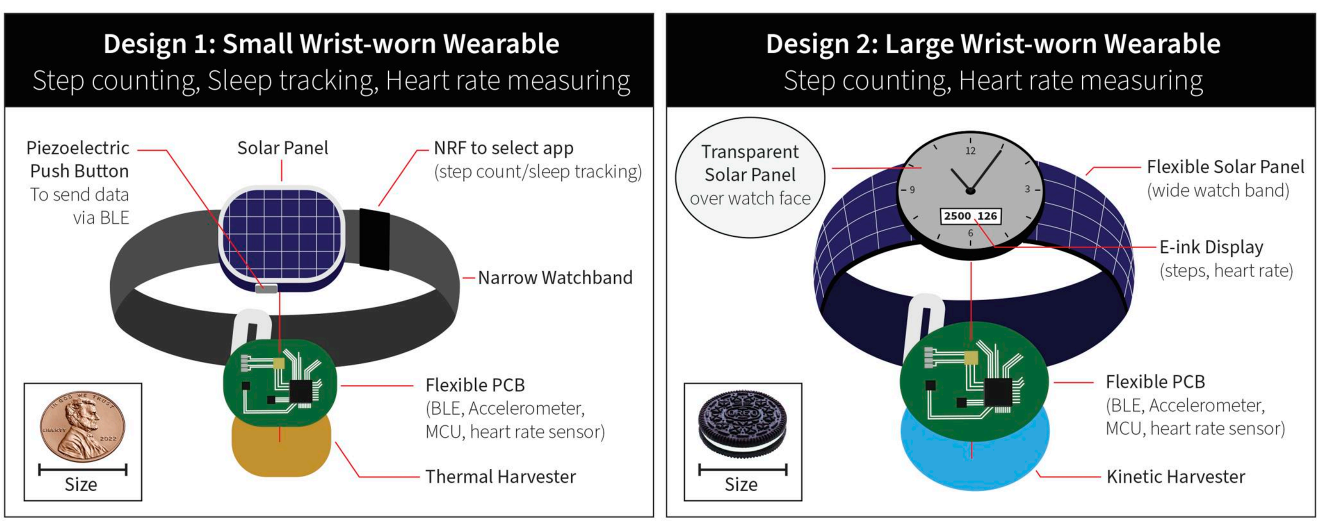


Figure 7. Proposed example of user-centric designs for wrist-worn batteryless devices.

information collected. For instance, if they notice inaccuracy/lack of data during certain periods, they can identify reasons for the inactivity, such as the solar/kinetic-powered activity tracker being covered by a sleeve while sitting in the office or placed in a dark location like a drawer. By incorporating such a feature, developers can enhance user trust and engagement with the batteryless wearable, as users become more confident in interpreting and utilizing the data it provides. This approach fosters a greater sense of control and comprehension, encouraging more active and meaningful engagement with the device's capabilities.

5.2. Convenient and sustainable daily sensing applications

While the participants in our study were open to using batteryless wearables for a variety of sense applications (with the exception of tone analysis, although it is used in a commercial wearable to support mental health, this purpose was not clear to the participants), we caution the designers of batteryless wearables against implementing too many applications in parallel (de Winkel et al., 2021). This is because supporting multiple applications requires more power, which in turn would require larger harvesters. This will inevitably require increasing the size of the device—potentially beyond the ideal upper limit of the "small" device (the size of an Oreo cookie) tested in our study. A similar trade-off also occurs in battery-powered devices, where power-hungry applications require either a larger device or more frequent charging. Thus, developers of batteryless wearables must intelligently enable/disable applications based on the context using event-driven techniques or allow users to control which applications are activated at any time. For example, the wearable could (allow the user to) disable sleep tracking during the day and (allow the user to) disable fitness tracking at night using zero energy interaction techniques, e.g., NFC or Piezoelectric push buttons as illustrated in Design 1, Figure 7. In addition, developers must use an ultra-low-power sensor to support multiple applications instead of using multiple sensors when it is possible. For instance, the heart rate sensor can be used to measure the heart rate/blood pressure as well as the user's mental state based on heart rate variability (HRV) instead of relying on tone analysis which raised a privacy concern among our participants.

Despite the inherent limitations of batteryless wearables, our results highlight several applications where batteryless wearables are advantageous over battery-powered devices. These considerations can inform the design of new wearable devices.

5.2.1. Convenient Non-Stop activity tracking

Participants in our study found batteryless activity trackers (e.g., step counting) more desirable than those powered by batteries. Users who are motivated to track their activity tend to wear their device during most of the day, and they do not want the tracking to be interrupted because of a battery that must be recharged or replaced. Activity trackers are an ideal use case for batteryless wearables, as the movement that is being tracked is, at the same time, a rich source for harvesting energy. If implemented correctly, an activity tracker without batteries can motivate people to be more active since it will always be ready to use when the user needs it to be.

5.2.2. Eco-Friendly heart rate monitoring and sleep tracking with advanced energy harvesting

In our study, participants found heart rate monitoring and sleep tracking to be useful applications; however, they expressed concerns about the eco-friendliness of these applications. This is likely because both activities generate little to no energy, and measuring heart rate requires energy even when the user is at rest, making it necessary to supplement the power source. However, recent research has found a new way to harvest energy continuously from the user's fingertips during sleep (Yin et al., 2021), which can be transferred to a wrist- or finger-worn batteryless device using a technique proposed in (Shukla et al., 2019). Additionally, advanced thermal harvesters such as MATRIX Prometheus (Matrix Industries, n.d.) can convert small temperature gradients into useful electricity, which can provide enough power for sleep tracking, particularly as people tend to sleep in a cold ambient temperature (Okamoto-Mizuno & Mizuno, 2012). The first wrist-worn design in Figure 7 demonstrates how these novel technologies can enable sleep tracking with the same benefits as described above for activity tracking: instantaneous availability with no need for inconvenient and environmentally unfriendly batteries or any external equipment (like an RF transmitter to power RF Bandaid, as discussed in Ranganathan et al. (2018)).

Similarly, using thermal harvesters can enable continuous heart rate monitoring without the need for supplementary batteries or the user having to perform physical activities to generate kinetic energy to power the device, as studied in Bose et al. (2020). These advances in energy harvesting technology can help overcome the energy limitations of heart rate monitoring and sleep tracking, enabling the development of eco-friendly wearable devices with sustainable power sources.

5.3. Convenient and energy efficient body placement

While the efficient body placement for harvesting kinetic energy in a batteryless device is typically the user's wrist or ankle (Cai & Liao, 2021; Halim et al., 2018), our study revealed that participants from both groups found wearing the device on the wrist more convenient than on the ankle. This preference is rooted in social and cultural considerations (Kilgour, 2020), as well as the familiarity established through the prevalent use of wrist-worn devices driven by commercial wearables. This location not only supports many sensing applications Zeagler (2017) but also offers efficient energy harvesting from various sources (Chong et al., 2019) and perceived less effort and attention among our participants (arguably because they can be operated/inspected more easily).

Interestingly, participants in both groups perceived arm-worn devices powered by harvested energy to be more convenient, and participants who received a tutorial also found them more useful than their battery-powered counterparts. This introduces an alternative to wrist-worn placements and provides developers with the flexibility to increase the device's size beyond that of an Oreo cookie-the larger size favored in our study. Enlarging the device allows for the incorporation of larger or multiple harvesters, capturing more energy, extending the device operation, supporting multiple applications, and performing more computations. This body placement is particularly advantageous for harvesters that demand larger dimensions to generate sufficient energy, such as flexible thermal harvesters (Proto et al., 2021). The concern about user comfort with a larger-sized device is mitigated by the fact that many individuals already wear items like phones on their arms during physical activities. However, the designer must minimize the weight of the wearable in this place as wearing bulky or heavy wearables on the body's extremities for a prolonged duration can lead to discomfort, restricted movement, and potential strain (Zeagler, 2017). To address this concern, a solution lies in the utilization of flexible energy harvesters, customized flexible circuit boards, and soft, comfortable materials for wearable bands. These components contribute to enhanced user comfort and minimize potential discomfort or stress caused by long-term wear.

5.4. The inevitable data synchronization and storage trade-offs

Our findings indicate that participants perceive NFC to be more effortful and attention-demanding, less convenient, and less useful than Bluetooth; however, when wearables are powered by harvested energy, participants anticipate NFC to require less effort and attention for data synchronization than Bluetooth. Each method has its own drawbacks. With Bluetooth, since batteryless wearables cannot establish a full "handshake"-style synchronization connection (i.e., they rely on passive communication), users would always have to have the wearable smartphone app running in the background to avoid data loss. Unfortunately, mobile operating systems tend to kill background processes to save the phone's battery and memory (Hu et al., 2014). As an alternative, developers could schedule the Bluetooth scanning process, but even this method is not fully reliable, as mobile operating systems can modify the schedule based on factors like app usage and resources budget (i.e., battery, memory, and scheduled tasks for other applications) (Apple Inc, n.d.). As such, it is nearly impossible to support Bluetooth synchronization without at least some data loss. Although recent work (De Winkel et al., 2022) attempts to enable the "handshake"-style synchronization connection and save it to the batteryless device's non-volatile FRAM to maintain the connection across the power outages, it works under the assumption that the mobile device application is scanning for the batteryless device at the same time when the batteryless device has enough power to successfully establish the connection for the first time which is not always the case under low harvested energy condition.

On the other hand, NFC does not have this problem, as it inherently leverages a passive connection. However, NFC requires the user to hold the phone close to the wearable every time they want to synchronize it—an inconvenience that is arguably exacerbated if the device is worn in an inconvenient place on the body.

Piezoelectric buttons could provide a solution to sending data through Bluetooth (cf. (Tan et al., 2006)), since these buttons can serve as a means to initiate the synchronization as well as a means to harvest the power required for sending the data to the phone as illustrated in the first suggested design, Figure 7. Other alternative option involves directing the phone's flashlight towards the solar cell in cases where the device incorporates such a harvester, as demonstrated in the smart microCard where Bluetooth packets are transmitted upon the user exposing the solar cell to a specific level of light (Gomez, 2020). However, these methods transform data synchronization into a manual procedure instead of passive, albeit offering on-demand synchronization.

Wearables that rely on cloud storage and data processing cause privacy concerns and require the user to always have an active Internet connection. As such, we suggest that designers should consider storing and processing the data locally on the user's phone, even though this poses a risk in case the phone is stolen, lost, or reset without a backup (cf. (Kobsa et al., 2014)). Developers can balance this trade-off by providing users with the option to make encrypted cloud backups or backups on another personal device like a computer. Encryption would also be desired for sending collected data to others, e.g., exercise peers or healthcare professionals.

5.5. Use E-ink screens, but be mindful of privacy and disruptions

Our quantitative analysis revealed that screenless devices offer greater convenience and decreased privacy concerns for users, which is advantageous for batteryless wearables. However, our qualitative data indicated that many participants expressed a desire for some form of display on their wearables to keep them informed about their sensed data, rather than having to check their phones frequently. Equipping a batteryless device with an LCD screen is not feasible due to its high power consumption. Therefore, we recommend designers of batteryless wearables consider an e-ink display. Not only are such displays more power efficient, but they also retain the last updated information when they lose power. This makes them uniquely suitable for batteryless wearables.

A notable downside of e-ink displays in batteryless wearables is that their always-on nature may give users the feeling that the system is on when it is not (de Winkel et al., 2021) and continuously consuming power which is not. When the system is off, an e-ink display maintains the last updated information, which could be outdated by the time the user inspects the display—something that could lead to confusion unless the user is aware of it. In addition, e-ink displays pose a potential threat to privacy: Unlike most wearable LCDs, they do not turn off when the user stops attending to them. As such, e-ink displays may easily reveal the last updated piece of information to bystanders, even when they lose power.

Smaller screens use less power, so we recommend that batteryless wearable developers think of creative ways to incorporate tiny displays into larger devices. For example, one could embed a tiny e-ink display into a physical watch face (e.g. in the place where classical watches show a mechanical date counter), in order to show tiny pieces of information such as steps taken or current heart rate as illustrated in the second design, Figure 7. The watch itself can also be powered by harvested energy (cf. the Seiko Kinetic watch (Seikowatches, n.d.)). Moreover, rather than updating the display at unpredictable intervals when the harvested power is sufficient, one could save power by only updating it at the user's explicit request (e.g. using NFC on the user phone as in Dierk et al. (2018) or by pushing a piezoelectric button (Tan et al., 2006) which can also provide the energy needed to update the e-ink content). Similarly, these approaches could be used to enable privacy-conscious users to clear any sensitive information from the e-ink display e.g., a double button push updates the screen and a single button push clears it.

5.6. Educating users about the differences between batteryless devices and their counterparts

Our study found a misconception among users and a lack of knowledge when switching from battery-powered to batteryless wearables, and this necessitated educating them regarding design decisions.

Our study revealed that participants who did not receive the tutorial about batteryless seem to have a misunderstanding about the intermittent operation of these devices (although we highlighted this in the presented scenario as it only works when it has enough power), expecting it to be more accurate than the battery powered devices that required charging or replacement. This misconception might be biased by widely common commercial watches (e.g Seiko) that are powered by batteries (not capacitors). Those batteries are always charged by kinetic or thermal energy, enabling continuous operation as long as the device is worn. However, this misconception is cleared with participants who were informed about batteryless technology but a new misconception was raised about the working environment of certain harvesters such as solar, assuming it only works outdoors, despite that the tutorial emphasizes that it works both indoors and outdoors. Similarly, thermal harvesters are assumed to work only outdoors in cold weather. Furthermore, participants from this group also confused the charging rate of batteryless devices with that of devices with batteries. Our results suggest that users must be educated regarding the operation of the utilized harvester in various environmental conditions. Additionally, users should be informed about the differences between utilizing capacitors and batteries to store the harvested energy for powering wearable devices, particularly in terms of intermittent operation and charging rates.

The study also, revealed that the participants have expressed concerns regarding the intermittent operation of batteryless wearables for monitoring critical health conditions such as blood pressure. It is important to educate users that these devices are not designed to monitor critical health conditions, and battery-powered wearables may be a better option in such cases.

Our results indicate that individuals who were educated about the intermittent operation of batteryless were concerned about data reliability. However this is a valid concern but they need to be informed that even battery powered devices don't turn on the sensors always on all the time, instead, they sample them in a duty cycle manner to save the device battery life which might ease this concern.

Furthermore, the participants seem to assume that sleep tracking and heart rate monitoring are required a supplement battery, because they may be unaware of the advanced existence of thermal harvesters (Matrix Industries, n.d.) which could power batteryless sleep tracking/heart rate monitoring devices—educating users about this eco-friendly possibility would be a useful opportunity for those seeking to develop such a device.

Users also are unaware of the relationship between body position and the effectiveness of various types of harvesters. Therefore, if a batteryless device uses a harvester that requires unconventional body placement, it may be crucial to educate users about this design decision.

Finally, users' display type preferences are not different for batteryless and battery-powered devices. However, some participants think that e-ink wastes stored power (since the information is always displayed). Again, users of novel batteryless devices may have to be educated about this type of display.

6. Limitations and future work

The goal of our study is to get users' perspectives on the design characteristics of batteryless wearables. We conducted this study on Prolific, an online crowdsourcing platform whose users may not be a representative sample. To increase the alignment between our sample and the target population, we specifically recruited participants who owned a smartwatch or fitness tracker (Prolific has a built-in tool to screen for these characteristics).

Another drawback of our study is that participants provided opinions about scenarios describing wearable devices—they did not interact with the described devices. However, this work was an attempt to narrow down the design possibilities by studying a broad set of parameters that can play a role in the design of batteryless wearables and highlight unique design opportunities. Future research should consider conducting further studies on users' perceptions of batteryless wearables, including qualitative studies (e.g. interviews and focus groups) to obtain deeper insights about users' perceptions, or live studies with functional prototypes designed based on the results of our study.

7. Conclusion

Batteryless wearables are new types of wearables that may have unique drawbacks and advantages compared to their battery-powered counterparts. Our study provides valuable insights into how users perceive the pros (e.g., no charging) and cons (e.g., intermittent operation) of such devices in the context of possible sensing applications, body positions, display types and sizes, and data storage and synchronization options. As such, our paper provides suggestions for the developers of batteryless wearables addressing the challenges and trade-offs in designing usable and scalable batteryless wearables.

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ORCID

Arwa Alsubhi http://orcid.org/0000-0003-3912-8143
Reza Ghaiumy Anaraky http://orcid.org/0000-0003-2405-3695
Simeon Babatunde http://orcid.org/0000-0003-0493-5834
Abu Bakar http://orcid.org/0000-0003-0757-7454
Thomas Cohen http://orcid.org/0009-0004-2259-3393
Josiah Hester http://orcid.org/0000-0002-1680-085X
Jacob Sorber http://orcid.org/0000-0003-0097-9282

References

Abedin, A., Rezatofighi, S. H., Shi, Q., & Ranasinghe, D. C. (2019). *Sparsesense: Human activity recognition from highly sparse sensor data-streams using set-based neural networks* [Paper presentation]. International Joint Conference on Artificial Intelligence (pp. 5780–5786).

Aboutamazon (2020). *Introducing amazon halo and amazon halo band-a new service that helps customers improve their health and wellness.* Press Center. https://press.aboutamazon.com/2020/8/introducing-amazon-halo-and-amazon-halo-band-a-new-service-that-helps-customers-improve-their-health-and-wellness

Agezo, Z., Ye, C., & Vora, S., & Kurzweg, T. (2016). *Battery-free rfid heart rate monitoring system* [Paper presentation]. 2016 IEEE Wireless Health (wh) (pp. 1–7). https://doi.org/10.1109/WH.2016.7764568

Alsubhi, A., Tobias, N., Babatunde, S., & Sorber, J. (2020). *Can crystal oscillators keep time without power?* [Paper presentation]. Proceedings of the 8th International Workshop on Energy Harvesting and Energy-Neutral Sensing Systems (pp. 84–85). https://doi.org/10.1145/3417308.3430278

Apple Inc. (n.d.). *Background execution demystified - wwdc20 - videos.* https://developer.apple.com/videos/play/wwdc2020/10063

Arora, N., Zhang, S. L., Shahmiri, F., Osorio, D., Wang, Y.-C., Gupta, M., Wang, Z., Starner, T., Wang, Z. L., & Abowd, G. D. (2018). Saturn: A thin and flexible self-powered microphone leveraging triboelectric nanogenerator. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *2*(2), 1–28. https://doi.org/10.1145/3214263

Bassett, D. R., Toth, L. P., LaMunion, S. R., & Crouter, S. E. (2017). Step counting: A review of measurement considerations and health-related applications. *Sports Medicine*, *47*(7), 1303–1315. https://doi.org/10.1007/s40279-016-0663-1

Boada, M., Lazaro, A., Villarino, R., & Girbau, D. (2019). Battery-less nfc sensor for ph monitoring. *IEEE Access*. *7*, 33226–33239. https://doi.org/10.1109/ACCESS.2019.2904109

Bose, S., Shen, B., & Johnston, M. L. (2020). A batteryless motion-adaptive heartbeat detection system-on-chip powered by human body heat. *IEEE Journal of Solid-State Circuits*, *55*(11), 2902–2913. https://doi.org/10.1109/jssc.2020.3013789

Cai, M., & Liao, W.-H. (2021). High-power density inertial energy harvester without additional proof mass for wearables. *IEEE Internet of Things Journal*, *8*(1), 297–308. https://doi.org/10.1109/JIOT.2020.3003262

Cho, H.-W., Yoon, J. H., Yoo, S.-S., Choi, B. G., & Yoo, H.-J. (2019). *A batteryless chronic wound monitoring system with NFC* [Paper presentation]. 2019 Ieee Eurasia Conference on Biomedical Engineering, Healthcare and Sustainability (Ecbios) (pp. 31–34). https://doi.org/10.1109/ECBIOS.2019.8807859

Chong, Y.-W., Ismail, W., Ko, K., & Lee, C.-Y. (2019). Energy harvesting for wearable devices: A review. *IEEE Sensors Journal*, *19*(20), 9047–9062. https://doi.org/10.1109/JSEN.2019.2925638

Cong, P., Ko, W. H., & Young, D. J. (2010). Wireless batteryless implantable blood pressure monitoring microsystem for small laboratory animals. *IEEE Sensors Journal*, *10*(2), 243–254. https://doi.org/10.1109/JSEN.2009.2030982

DeBruin, S., Ghena, B., Kuo, Y.-S., & Dutta, P. (2015). *Powerblade: A low-profile, true-power, plug-through energy meter* [Paper presentation]. Proceedings of the 13th Acm Conference on Embedded Networked Sensor Systems (pp. 17–29). https://doi.org/10.1145/2809695.2809716

de Winkel, J., Delle Donne, C., Yildirim, K. S., Pawełczak, P., & Hester, J. (2020). *Reliable timekeeping for intermittent computing* [Paper presentation]. Computing Machinery Proceedings of the Twenty-Fifth International Conference on Architectural Support for Programming Languages and Operating Systems (pp. 53–67). https://doi.org/10.1145/3373376.3378464

De Winkel, J., Kortbeek, V., Hester, J., & Pawełczak, P. (2020). Battery-free game boy. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *4*(3), 1–34. https://doi.org/10.1145/3411839

de Winkel, J., Kortbeek, V., Hester, J., & Pawełczak, P. (2021). Battery-free game boy: Sustainable interactive devices. *GetMobile: Mobile Computing and Communications*, *25*(2), 22–26. https://doi.org/10.1145/3486880.3486888

De Winkel, J., Tang, H., & Pawełczak, P. (2022). *Intermittently-powered bluetooth that works* [Paper presentation]. Proceedings of the 20th Annual International Conference on Mobile Systems, Applications and Services (pp. 287–301). https://doi.org/10.1145/3498361.3538934

Dierk, C., Nicholas, M. J. P., & Paulos, E. (2018). *Alterwear: Battery-free wearable displays for opportunistic interactions* [Paper presentation]. Proceedings of the 2018 Chi Conference on Human Factors in Computing Systems (pp. 1–11). https://doi.org/10.1145/3173574.3173794

Dierk, C., Vega Gálvez, T., & Paulos, E. (2017). *Alternail: Ambient, batteryless, stateful, dynamic displays at your fingertips.* [Paper presentation]. Proceedings of the 2017 Chi Conference on Human Factors in Computing Systems (pp. 6754–6759). https://doi.org/10.1145/3025453.3025924

Escobedo, P., Bhattacharjee, M., Nikbakhtnasrabadi, F., & Dahiya, R. (2021). Smart bandage with wireless strain and temperature sensors and batteryless nfc tag. *IEEE Internet of Things Journal*, *8*(6), 5093–5100. https://doi.org/10.1109/JIOT.2020.3048282

Faltaous, S., Altmeyer, M., Kosmalla, F., Lessel, P., Daiber, F., & Schneegass, S. (2021). *Understanding user requirements for self-created iot health assistant systems* [Paper presentation]. Proceedings of the 20th International Conference on Mobile and Ubiquitous Multimedia (pp. 43–55). https://doi.org/10.1145/3490632.3490645

Gomez, A. (2020). *On-demand communication with the batteryless mirocard: Demo abstract*. [Paper presentation]. Proceedings of the 18th Conference on Embedded Networked Sensor Systems (pp. 629–630). https://doi.org/10.1145/3384419.3430440

Halim, M. A., Rantz, R., Zhang, Q., Gu, L., Yang, K., & Roundy, S. (2018). *Modeling and experimental analysis of a wearable energy harvester that exploits human-body motion* [Paper presentation]. 2018 Ieee Sensors (pp. 1–4). https://doi.org/10.1109/ICSENS.2018.8589632

He, Y., Bahirat, P., Knijnenburg, B. P., & Menon, A. (2020). A data-driven approach to designing for privacy in household iot. *ACM Transactions on Interactive Intelligent Systems*, *10*(1), 1–47. https://doi.org/10.1145/3241378

Hendrickson, C., Lave, L., McMichael, F., Siewiorek, D., Smailagic, A., & Wu, T.-S. (1994). *Product disposal and re-use issues for portable computer design* [Paper presentation]. Proceedings of 1994 Ieee International Symposium on Electronics and the Environment (pp. 109–114). https://doi.org/10.1109/ISEE.1994.337297

Heo, S. Y., Kim, J., Gutruf, P., Banks, A., Wei, P., Pielak, R., Balooch, G., Shi, Y., Araki, H., Rollo, D., Gaede, C., Patel, M., Kwak, J. W., Peña-Alcántara, A. E., Lee, K.-T., Yun, Y., Robinson, J. K., Xu, S., & Rogers, J. A. (2018). Wireless, battery-free, flexible, miniaturized dosimeters monitor exposure to solar radiation and to light for phototherapy. *Science Translational Medicine*, *10*(470), eaau1643. https://doi.org/10.1126/scitranslmed.aau1643

Hester, J., Sorber, J. (2017a). Flicker: Rapid prototyping for the batteryless internet-of-things [Paper presentation]. Proceedings of the 15th Acm Conference on Embedded Network Sensor Systems (pp. 1–13). https://doi.org/10.1145/3131672.3131674

Hester, J., & Sorber, J. (2017b). *The future of sensing is batteryless, intermittent, and awesome* [Paper presentation]. Proceedings of the 15th Acm Conference on Embedded Network Sensor Systems (pp. 1–6). https://doi.org/10.1145/3131672.3131699

Hester, J., Tobias, N., Rahmati, A., Sitanayah, L., Holcomb, D., Fu, K., Burleson, W. P., & Sorber, J. (2016). Persistent clocks for batteryless sensing devices. *ACM Transactions on Embedded Computing Systems*, *15*(4), 1–28. https://doi.org/10.1145/2903140

Hu, G., Yuan, X., Tang, Y., & Yang, J. (2014). *Efficiently, effectively detecting mobile app bugs with appdoctor* [Paper presentation]. Proceedings of the Ninth European Conference on Computer Systems (pp. 1–15). https://doi.org/10.1145/2592798.2592813

Huang, Q., Mei, Y., Wang, W., & Zhang, Q. (2018). Toward battery-free wearable devices: The synergy between two feet. *ACM Transactions on Cyber-Physical Systems*, *2*(3), 1–18. https://doi.org/10.1145/3185503

Izonin, I., Kryvinska, N., Tkachenko, R., & Zub, K. (2019). An approach towards missing data recovery within iot smart system. *Procedia Computer Science*, *155*, 11–18. https://doi.org/10.1016/j.procs.2019.08.006

Jaiswal, D., Gigie, A., Chakravarty, T., Ghose, A., & Misra, A. (2018). *Table of interest: Activity recognition and behaviour analysis using a battery less wearable sensor* [Paper presentation]. Proceedings of the 4th ACM Workshop on Wearable Systems and Applications (pp. 39–44). https://doi.org/10.1145/3211960.3211976

Jayatilaka, A., Dang, Q. H., Chen, S. J., Visvanathan, R., Fumeaux, C., & Ranasinghe, D. C. (2019). *Designing batteryless wearables for hospitalized older people* [Paper presentation]. Proceedings of the 23rd International Symposium on Wearable Computers (pp. 91–95). https://doi.org/10.1145/3341163.3347740

Jeong, H., Kim, H., Kim, R., Lee, U., & Jeong, Y. (2017). Smartwatch wearing behavior analysis: A longitudinal study. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *1*(3), 1–31. https://doi.org/10.1145/3131892

Kalantarian, H., & Sarrafzadeh, M. (2016). Pedometers without batteries: An energy harvesting shoe. *IEEE Sensors Journal*, *16*(23), 1–1. https://doi.org/10.1109/JSEN.2016.2591331

Kickstarter (2018). *Lunar, the world's first solar powered smartwatch*. https://www.kickstarter.com/projects/lunarsmartwatch/lunar-the-worlds-first-solar-powered-smartwatch

Kilgour, L. (2020). The ethics of aesthetics: Stigma, information, and the politics of electronic ankle monitor design. *The Information Society*, *36*(3), 131–146. https://doi.org/10.1080/01972243.2020.1737606

Kim, K. J. (2017). Shape and size matter for smartwatches: Effects of screen shape, screen size, and presentation mode in wearable communication. *Journal of Computer-Mediated Communication*, *22*(3), 124–140. https://doi.org/10.1111/jcc4.12186

Kim, W.-G., Kim, D.-W., Tcho, I.-W., Kim, J.-K., Kim, M.-S., & Choi, Y.-K. (2021). Triboelectric nanogenerator: Structure, mechanism, and applications. *ACS Nano*, *15*(1), 258–287. https://doi.org/10.1021/acsnano.0c09803

Kinetron (n.d). *Mechanical generator systems*. https://www.kinetron.eu/mechanical

Kobsa, A., Knijnenburg, B. P., & Livshits, B. (2014). *Attitudinal and Behavioral Study of Privacy in Client-side Personalization* [Paper presentation]. Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Let'sDoIt atMyPlaceInstead? (pp. 81–90). ACM. http://doi.org/10.1145/2556288.2557102

Lazaro, A., Boada, M., Villarino, R., & Girbau, D. (2019). Battery-less smart diaper based on nfc technology. *IEEE Sensors Journal*, *19*(22), 10848–10858. https://doi.org/10.1109/JSEN.2019.2933289

Li, Y., Li, T., Patel, R. A., Yang, X.-D., & Zhou, X. (2018). *Self-powered gesture recognition with ambient light* [Paper presentation]. Proceedings of the 31st Annual Acm Symposium on User Interface Software and Technology (pp. 595–608). https://doi.org/10.1145/3242587.3242635

Liu, X., Chen, T., Qian, F., Guo, Z., Lin, F. X., Wang, X., & Chen, K. (2017). *Characterizing smartwatch usage in the wild* [Paper presentation]. Proceedings of the 15th Annual International Conference on Mobile Systems, Applications, and Services (pp. 385–398). https://doi.org/10.1145/3081333.3081351

Magno, M., & Boyle, D. (2017). *Wearable energy harvesting: From body to battery* [Paper presentation]. 2017 12th International Conference on Design & Technology of Integrated Systems in Nanoscale Era (Dtis) (pp. 1–6). https://doi.org/10.1109/DTIS.2017.7930169

Magno, M., Brunelli, D., Sigrist, L., Andri, R., Cavigelli, L., Gomez, A., & Benini, L. (2016). Infinitime: Multi-sensor wearable bracelet with human body harvesting. *Sustainable Computing: Informatics and Systems*, *11*, 38–49. https://doi.org/10.1016/j.suscom.2016.05.003

Magno, M., Spadaro, L., Singh, J., & Benini, L. (2016). *Kinetic energy harvesting: Toward autonomous wearable sensing for internet of things* [Paper presentation]. 2016 International Symposium on Power Electronics, Electrical Drives, Automation and Motion (Speedam) (pp. 248–254). https://doi.org/10.1109/SPEEDAM.2016.7525995

Matrix Industries (n.d). *Technology-matrix: Self-powered solutions*. https://www.matrixindustries.com/technology

Monjur, M., & Nirjon, S. (2022). *An empirical analysis of perforated audio classification* [Paper presentation]. *Proceedings of* The 1st Acm International Workshop on Intelligent Acoustic Systems and Applications (pp. 25–30). https://doi.org/10.1145/3539490.3539602

Motti, V. G., & Caine, K. (2016). Smart wearables or dumb wearables? Understanding how context impacts the ux in wrist worn interaction [Paper presentation]. Proceedings of the 34th ACM International Conference on the Design of Communication (pp. 1–10). https://doi.org/10.1145/2987592.2987606

Myers, B. (1994). Challenges of hci design and implementation. *Interactions*, *1*(1), 73–83. https://doi.org/10.1145/174800.174808

Okamoto-Mizuno, K., & Mizuno, K. (2012). Effects of thermal environment on sleep and circadian rhythm. *Journal of Physiological Anthropology*, *31*(1), 14. https://doi.org/10.1186/1880-6805-31-14

Park, H., & McKilligan, S. (2018). *A systematic literature review for human-computer interaction and design thinking process integration* [Paper presentation]. International Conference of Design, User

Experience, and Usability (pp. 725–740). https://doi.org/10.1007/978-3-319-91797-9_50

Parrilla, M., & De Wael, K. (2021). Wearable self-powered electrochemical devices for continuous health management. *Advanced Functional Materials*, *31*(50), 2107042. https://doi.org/10.1002/adfm.202107042

Paul, G., & Irvine, J. (2014). *Privacy implications of wearable health devices* [Paper presentation]. Proceedings of the 7th International Conference on Security of Information and Networks (pp. 117–121). https://doi.org/10.1145/2659651.2659683

Pecunia, V., Silva, S. R. P., Phillips, J. D., Artegiani, E., Romeo, A., Shim, H., … Welch, G. C. (2023). Roadmap on energy harvesting materials. *Journal of Physics: Materials*, *6*(4), 042501. https://doi.org/10.1088/2515-7639/acc550

Powerwatch (n.d). *Series 2.* https://www.powerwatch.com/products/powerwatch-2

Proto, A., Vondrak, J., Schmidt, M., Kubicek, J., Gorjani, O. M., Havlik, J., & Penhaker, M. (2021). A flexible thermoelectric generator worn on the leg to harvest body heat energy and to recognize motor activities: A preliminary study. *IEEE Access*. *9*, 20878–20892. https://doi.org/10.1109/ACCESS.2021.3054405

Rahmati, A., Salajegheh, M., Holcomb, D., Sorber, J., Burleson, W. P., & Fu, K. (2012). *Tardis: Time and remanence decay in sram to implement secure protocols on embedded devices without clocks* [Paper presentation]. Proceedings of the 21st Usenix Conference on Security Symposium (pp. 36–36).

Ranganathan, V., Gupta, S., Lester, J., Smith, J. R., & Tan, D. (2018). Rf bandaid: A fully-analog and passive wireless interface for wearable sensors. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *2*(2), 1–21. https://doi.org/10.1145/3214282

Ryokai, K., Su, P., Kim, E., & Rollins, B. (2014). *Energybugs: Energy harvesting wearables for children* [Paper presentation]. Proceedings of the Sigchi Conference on Human Factors in Computing Systems (pp. 1039–1048). https://doi.org/10.1145/2556288.2557225

Seikowatches (n.d). Kinetic|Knowledge|CustomerService|SeikoWatch Corporation https://www.seikowatches.com/us-en/customerservice/knowledge/kinetic-knowledge

Seneviratne, S., Hu, Y., Nguyen, T., Lan, G., Khalifa, S., Thilakarathna, K., Hassan, M., & Seneviratne, A. (2017). A survey of wearable devices and challenges. *IEEE Communications Surveys & Tutorials*, *19*(4), 2573–2620. https://doi.org/10.1109/COMST.2017.2731979

Shahu, A., Wintersberger, P., & Michahelles, F. (2022). *Would users accept electric muscle stimulation controlling their body? insights from a scenario-based investigation* [Paper presentation]. Chi Conference on Human Factors in Computing Systems Extended Abstracts (pp. 1–7). https://doi.org/10.1145/3491101.3519693

Shukla, R., Kiran, N., Wang, R., Gummeson, J., & Lee, S. I. (2019). *Skinnypower: Enabling batteryless wearable sensors via intra-body power transfer* [Paper presentation]. Proceedings of the 17th Conference on Embedded Networked Sensor Systems (pp. 68–82). https://doi.org/10.1145/3356250.3360034

Song, Y., Mukasa, D., Zhang, H., & Gao, W. (2021). Self-powered wearable biosensors. *Accounts of Materials Research*, *2*(3), 184–197. https://doi.org/10.1021/accountsmr.1c00002

Stuart, T., Kasper, K. A., Iwerunmor, I. C., McGuire, D. T., Peralta, R., Hanna, J., Johnson, M., Farley, M., LaMantia, T., Udorvich, P., & Gutruf, P. (2021). Biosymbiotic, personalized, and digitally manufactured wireless devices for indefinite collection of high-fidelity biosignals. *Science Advances*, *7*(41), eabj3269. https://doi.org/10.1126/sciadv.abj3269

Su, M., & Kim, B. (2020). Silk fibroin-carbon nanotube composites based fiber substrated wearable triboelectric nanogenerator. *ACS Applied Nano Materials*, *3*(10), 9759–9770. https://doi.org/10.1021/acsanm.0c01854

Talla, V., Kellogg, B., Gollakota, S., & Smith, J. R. (2017). Battery-free cellphone. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *1*(2), 1–20. https://doi.org/10.1145/3090090

Tan, Y., Hoe, K., & Panda, S. (2006). *Energy harvesting using piezoelectric igniter for self-powered radio frequency (rf) wireless sensors* [Paper presentation]. 2006 Ieee International Conference on Industrial Technology (pp. 1711–1716). https://doi.org/10.1109/ICIT.2006.372517

Truong, H., Zhang, S., Muncuk, U., Nguyen, P., Bui, N., Nguyen, A., … Vu, T. (2018). Capband: Battery-free successive capacitance sensing wristband for hand gesture recognition [Paper presentation]. Proceedings of the 16th Acm Conference on Embedded Networked Sensor Systems (pp. 54–67). https://doi.org/10.1145/3274783.3274854

Tuncel, Y., Bandyopadhyay, S., Kulshrestha, S. V., Mendez, A., & Ogras, U. Y. (2020). *Towards wearable piezoelectric energy harvesting: Modeling and experimental validation* [Paper presentation]. Proceedings of the ACM/IEEE International Symposium on Low Power Electronics and Design (pp. 55–60). https://doi.org/10.1145/3370748.3406578

Yan, J., Liao, X., Yan, D., & Chen, Y. (2018). Review of micro thermoelectric generator. *Journal of Microelectromechanical Systems*, *27*(1), 1–18. https://doi.org/10.1109/JMEMS.2017.2782748

Yin, L., Moon, J.-M., Sempionatto, J. R., Lin, M., Cao, M., Trifonov, A., Zhang, F., Lou, Z., Jeong, J.-M., Lee, S.-J., Xu, S., & Wang, J. (2021). A passive perspiration biofuel cell: High energy return on investment. *Joule*, *5*(7), 1888–1904. https://doi.org/10.1016/j.joule.2021.06.004

Zaidi, A., Yang, R., Koshy, V., Cobb, C., Gupta, I., & Karahalios, K. (2022). A user-centric evaluation of smart home resolution approaches for conflicts between routines. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *7*(1), 1–35. https://doi.org/10.1145/3581997

Zakaria, C., Foong, P. S., Lim, C. S., Vs Pakianathan, P., Koh, G. H. C., & Perrault, S. T. (2022). *Does mode of digital contact tracing affect user willingness to share information? a quantitative study* [Paper presentation]. Proceedings of the 2022 Chi Conference on Human Factors in Computing Systems (pp. 1–18). https://doi.org/10.1145/3491102.3517595

Zeagler, C. (2017*). Where to wear it: Functional, technical, and social considerations in on-body location for wearable technology 20 years of designing for wearability* [Paper presentation]. Proceedings of the 2017 Acm International Symposium on Wearable Computers (pp. 150–157). https://doi.org/10.1145/3123021.3123042

About the authors

Arwa Alsubhi is a Ph.D. candidate at Clemson University with a master's degree from the University of Wisconsin Milwaukee. Her research focuses on ultra-low-power and batteryless devices, with a keen interest in enhancing human-computer interaction within this cutting-edge technology landscape.

Reza Ghaiumy Anaraky is a Postdoctoral Associate at the Tandon School of Engineering at New York University. His research focuses on Human-Computer Interaction (HCI), information privacy, and aging. Reza's research has been recognized with several awards, including a Facebook Fellowship, three Best Paper awards, and an Innovative Research for Aging Award by Matter Institute.

Simeon Babatunde is a Ph.D. candidate at Clemson University. His research lies at the intersection of embedded networked sensor systems, intermittent computing, and Edge AI, primarily focusing on developing new low-power wireless network solutions to support emerging intermittent batteryless systems that operate entirely on harvested energy.

Abu Bakar is a PhD student at the School of Interactive Computing at Georgia Institute of Technology. His research interests are in low-power, battery-free intermittent computing systems. He explores new hardware designs and runtime systems to make on-device inference with energy-aware adaptation possible in extreme energy harvesting conditions. http://abubakar.info/.

Thomas Cohen is a mechanical engineer and graphic designer on staff at Northwestern University. He has been involved in research focused

on the design of health sensing wearable and battery-free devices. His scientific figures and graphics have been included in several publications.

Josiah Hester is an Associate Professor of Interactive Computing and Computer Science at the Georgia Institute of Technology. His research interests span computer systems and human-computer interaction applied to health, interactivity, and sustainability. He works toward a sustainable future for computing informed by his Native Hawaiian heritage.

Bart Knijnenburg is an Associate Professor in Human-Centered Computing and an expert in privacy decision-making and the user-centric evaluation of adaptive decision-support systems. His NSF CAREER research on recommender systems includes a conceptual framework and practical guidelines for user-centric evaluation that has become the de-facto standard in the field.

Jacob Sorber is a Professor in the School of Computing at Clemson University. His work makes mobile sensors and embedded systems more efficient, robust, deployable, and secure, by exploring novel systems (both hardware and software) and languages.

Appendices

Appendix A. Dependent variables used to evaluate each scenario and their tests analysis results

A1. Price expectation

Participants expressed the price they would be willing to pay for the presented wearables in US Dollars. We analyzed the responses using linear mixed effects regression (lme) with a random intercept to account for the fact that each participant rated 12 scenarios. Table A3 shows the effects of the scenario parameters on the price participants were willing to pay for the presented wearable[2]. The individual differences in price seem to overshadow any effects from the device application, as 60.90%, 65.10% of the variance in price is explained by the random intercept alone in both tutorial and no tutorial samples respectively.

In no tutorial sample, the main device application has the most substantial effect on price, explaining 3.15% of the variance in price, followed by the device power source which explains 1.60% of the variance in price. The device display, also contributes significantly to the price participants were willing to pay, but make only a small contribution (a increase in the explained variance of about 0.54%).

In the tutorial sample, similarly, the main device application has the most substantial effect on price, explaining 2.87% of the variance in price. The device power, display and where it is worn, also contribute significantly to the price participants were willing to pay, but make only a small contribution (a total increase in the explained variance of about 1.65%).

A2. Perceived usefulness

We measured the perceived usefulness of the described wearable device using a 7-point Likert-type question and analyzed it using linear mixed effects regression (lme). Among participants who were not educated about batteryless, we found that the way a wearable device is powered, its main application, body placement, and its display significantly contribute to its perceived usefulness among the participants who were not educated about batteryless. The main application has the strongest effect, explaining about 32.53% of the variance in usefulness. The device's power source, display, and body position make much smaller contributions (0.53% to 1.42% increase in explained variance). We also found a significant interaction effect between the device's power and its application in determining its perceived usefulness. Note, though, that this effect makes only a small contribution to predicting perceived usefulness (offering R-squared 0.44% increase); see Table A4.

In contrast, participants who were educated about batteryless did not find the way the device is powered significantly contributed to its perceived usefulness. Instead, the device's main application, body placement, display, and the way it syncs the data to the phone significantly contribute to its perceived usefulness. Similar to the none educated group, the main application has the strongest effect, explaining about 23.46% of the variance in usefulness. In comparison, other parameters make much smaller contributions (0.12% to 1.25% increase in

Table A1. Dependent variables and survey questions used to evaluate each scenario.

Dependent variable	Question	Scale
Price expectation	how much would you pay for this device?	US dollars
Perceived usefulness	How useless or useful is this device?	7-point scale
Perceived Convenience	How cumbersome or convenient is this device?	7-point scale
Expected performance	How effective do you expect this device to work?	7-point scale
Perceived Eco-friendliness	This device is___for the environment.	7-point scale
Perceived Accuracy	How accurate do you think the data is that this device collects?	7-point scale
Privacy concern perception	Using this device would cause me serious privacy problems.	7-point scale
Perceived Effort and attention	This device requires___of my attention and effort.	5- point scale
Upgrade intention	How often would you plan to upgrade a device like this?	6 options

Table A2. Effect of scenario parameters on the wearable expected price (no tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
Price ~(1—sid)			0.651089		
+power	3	104.80626	0.6671495	0.0160605	<.0001
+application	3	221.72848	0.6987316	0.0315821	<.0001
+body position	3	1.86411	0.698984	0.0002524	0.6011
+display	6	43.31120	0.7044489	0.0054649	<.0001
+data synchronization	1	0.05088	0.7044557	0.0000068	0.8215
+data storage	1	0.02053	0.7044576	0.0000019	0.8861

Table A3. Effect of scenario parameters on the wearable expected price (tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	P-Value
Price ~(1—sid)			0.604523		
+power	3	25.02374	0.6090581	0.0045351	<.0001
+application	3	165.78360	0.6378171	0.028759	<.0001
+body position	3	29.89258	0.6427729	0.0049558	<.0001
+display	6	44.39507	0.6499657	0.0071928	<.0001
+data synchronization	1	5.51476	0.6508579	0.0008922	0.0189
+data storage	1	0.05100	0.6508661	0.0000082	0.8213

Table A4. Effect of scenario parameters on the wearable perceived usefulness (no tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	P-Value
usefulness ~(1—sid)			0.1467666		
+power	3	28.5730	0.157653	0.0108863	<.0001
+application	3	1086.0090	0.4829551	0.3253021	<.0001
+body position	3	23.0426	0.4882818	0.0053266	<.0001
+display	6	59.7484	0.5025816	0.0142997	<.0001
+data synchronization	1	0.2722	0.5026425	0.0000609	0.6018
+data storage	1	0.0827	0.5026589	0.0000164	0.7736
Interactions					
+power:application	9	21.75216	0.5071119	0.0044529	0.0097

Table A5. Effect of scenario parameters on the wearable perceived usefulness (tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
usefulness ∼(1—sid)			0.2093162		
+power	3	6.5741	0.2117079	0.0023917	0.0868
+application	3	766.8625	0.4463746	0.2346667	<.0001
+body position	3	26.5244	0.4531003	0.0067257	<.0001
+display	6	54.0993	0.4656768	0.0125765	<.0001
+data synchronization	1	5.1431	0.466947	0.0012702	0.0233
+data storage	1	0.2059	0.4669976	0.0000506	0.6500
Interactions					
+power:body position	9	24.14036	0.4740053	0.0070077	0.0041

Table A6. Effect of scenario parameters on the wearable perceived convenience (both tutorial/no tutorial samples).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
Convenience ∼(1—sid)			0.1769648		
+tutorial	1	0.0821	0.1769663	0.0000015	0.7745
+power	3	54.8254	0.1871669	0.0102006	<.0001
+application	3	256.9042	0.2333073	0.0461404	<.0001
+body position	3	77.6044	0.2467231	0.0134158	<.0001
+display	6	844.3287	0.37932	0.1325969	<.0001
+data synchronization	1	5.7229	0.380126	0.000806	0.0167
+data storage	1	0.4288	0.380188	0.000062	0.5126
Interactions					
+power:body position	9	22.43866	0.3837211	0.0019253	0.0076

explained variance). We also found a significant interaction effect between the device's power and where it is worn on its perceived usefulness. Note, though, that this effect makes only a small contribution to predicting perceived usefulness (offering R-squared 0.70% increase; see Table A5.

A3. Perceived convenience

We measured the perceived convenience of the described wearable device using a 7-point Likert-type question and analyzed it using linear mixed effects regression (lme). In both groups, We learned that a wearable display has the most substantial effect on convenience, explaining 13.25% of its variance. The main application of the device is responsible for 4.61% of its variance on the perceived convenience, while its power source, its body placement, and how it syncs data to the user's phone have a significant but small impact on convenience, explaining 1.02%, 1.34%, and 0.08% of the variance, respectively.

We found a significant interaction effect between the device power source and where it is worn on the device's perceived convenience. However, this effect makes only a small contribution to predicting perceived usefulness (offering R-squared 0.19% increase); see Table A6.

A4. Expected performance of the wearable

Using a 7-point Likert-type item ranging from "very poorly" to "very well", we examined participants' expectations about how effective the device would work. We analyzed the results of this variable using a linear mixed effects regression (lme). For the group who did not receive the presurvey tutorial about batteryless, we found that a wearable device's expected performance is influenced by four factors: power source, main application, worn position on the body, and type and size of the display (see Table A7). The device's main application has the most substantial effect, explaining 11.40% of the variance in expected performance, while the device's power, body position, and display contribute only 0.34%, 1.66% and 1.09% respectively. On the other hand, for the group who received the batteryless tutorial, the power no longer significantly contributed to the perceived performance. Instead, how the device syncs the data to the users' phones influences the device's expected performance, explaining 0.17% of the variance. (see Table A8)

Looking at the potential two-way interaction effects between how the wearable is powered and other parameters in our study on expected

Table A7. Effect of scenario parameters on the wearable's expected performance (no tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	P-Value
Performance ∼(1—sid)			0.2601625		
+power	3	10.3360	0.2635915	0.003429	0.0159
+application	3	374.4890	0.3776713	0.1140798	<.0001
+body position	3	60.3923	0.3943364	0.0166651	<.0001
+display	6	38.7410	0.405246	0.0109096	<.0001
+data synchronization	1	0.0271	0.4052533	0.000007	0.8692
+data storage	1	0.5105	0.4053939	0.0001406	0.4749

Table A8. Effect of scenario parameters on the wearable's expected performance (tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
Performance ∼(1—sid)			0.2669963		
+power	3	7.42685	0.2695007	0.0025044	0.0595
+application	3	281.95736	0.3585085	0.0890078	<.0001
+body position	3	33.79263	0.3684207	0.0099122	<.0001
+display	6	45.67308	0.3810113	0.0125906	<.0001
+data synchronization	1	5.97398	0.3827168	0.0017055	0.0145
+data storage	1	0.00224	0.3827175	0.0000007	0.9622

Table A9. Effect of scenario parameters on the wearable's perceived eco-friendliness (both tutorial and no tutorial samples).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
Eco-friendliness ∼(1—sid)			0.2583686		
+tutorial	1	0.5904	0.2583759	0.0000073	0.4423
+power	3	1159.4389	0.430312	0.1719361	<.0001
+application	3	21.5816	0.4331021	0.0027901	0.0001
+body position	3	11.6198	0.4345986	0.0014965	0.0088
+display	6	80.9916	0.4450525	0.0104539	<.0001
+data synchronization	1	0.8830	0.4451637	0.0001112	0.3474
+data storage	1	0.0422	0.4451692	0.0000055	0.8373
Interactions					
+power:application	9	21.34927	0.4479786	0.0028094	0.0112

performance for both groups, we found no significant interaction effect.

A5. Perceived eco-friendliness

We assessed the perceived eco-friendliness of the wearable device using a 7-point Likert-type question ranging from "very unfriendly" to "very friendly" to the environment and performed a linear mixed effect regression (lme) on the results. The device's power source is a major factor influencing participants' perceptions of eco-friendliness, explaining 17.19% of the variance in eco-friendliness perceptions in both groups. The wearable device's screen, main application, and placement on the user's body also have significant but much smaller effects on the device's perceived eco-friendliness (explaining between 0.14% and 1.04% of the variance in perceived eco-friendliness, see Table A9). We found an interaction effect between the device power and its application explains a small (R-squared increase of 0.28%) but significant proportion of the variance in perceived eco-friendliness.

A6. Perceived accuracy

We measured the perceived main application accuracy of the presented wearable device by asking participants if they expected the device to be less accurate than, on par with, or more accurate than most other wearables. We coded these options −1, 0, and 1, respectively, and then performed a linear mixed effect regression (lme) on the results. Among the group who were not educated about batteryless technology, we found that the device's perceived accuracy is significantly and substantially affected by its main application (explaining 4.87% of the variance in perceived accuracy), while the device's power and body position

Table A10. Effect of scenario parameters on the perceived main application accuracy of the wearable (no tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
Accuracy ∼(1—sid)			0.1940124		
+power	3	12.12923	0.1983935	0.0043811	0.0070
+application	3	139.72326	0.2471769	0.0487834	<.0001
+body position	3	55.86779	0.2658415	0.0186646	<.0001
+display	6	6.85474	0.2676776	0.0018361	0.3345
+data synchronization	1	0.00064	0.2676778	0.0000002	0.9798
+data storage	1	1.01386	0.2680061	0.0003283	0.3140

Table A11. Effect of scenario parameters on the perceived main application accuracy of the wearable (tutorial sample).

Model	df	Chi-squared	R-squared	Δ R-squared	P-Value
Accuracy ∼(1—sid)			0.1593487		
+power	3	3.34144	0.1606419	0.0012932	0.3419
+application	3	86.49068	0.1934327	0.0327908	<.0001
+body position	3	27.56331	0.203611	0.0101783	<.0001
+display	6	8.47470	0.2067145	0.0031035	0.2053
+data synchronization	1	2.88284	0.2077662	0.0010517	0.0895
+data storage	1	0.31358	0.2078806	0.0001144	0.5755

played significant but smaller roles, explaining 0.43% and 1.33% of the variance respectively; see Table A10).

In contrast, among the participants who received the pre-survey tutorial about batteryless technology, the device's perceived accuracy is still significantly affected by its main application and where it's worn (explaining 3.27% and 1.01% of the variance). The device power no longer contributes to the perceived accuracy. see Table A11).

A7. Privacy concern

The perceived privacy concern caused by the presented device was measured using a 7-point Likert-type question. We analyzed participants' responses (in both groups) using a linear mixed effect regression (lme). The main application of the device has the most significant effect on privacy concerns, explaining 4.98% of the variance in privacy concerns (see Table A12). The data storage approach and display type have significant but smaller effects (explaining 1.07% and 0.44% of the variance in privacy concerns, respectively). No interaction effects between how the device is powered, and other scenario parameters were found to have a significant effect on users' privacy concerns.

A8. Perceived effort and attention

We evaluated the perceived effort and attention required by the presented device using a 5-point Likert-type item and analyzed the results using a linear mixed effects regression (lme). The effort and attention required to operate the device (in both groups) significantly depend on how the device is powered, where the device is worn on the user's body, the device display type and size, and where the how data is synced to the user's phone (see Table A13. The display and the power play the most significant role, explaining 3.73% and 3.25% respectively of the variance in effort and attention. The body position contributes 0.34% and data synchronization 0.07%. There is a small but significant interaction effect between the device power source and how the data syncs to the user's phone on users' perceptions of effort and attention, explaining 0.16% of the variance.

Table A12. Effect of scenario parameters on users' privacy concern (both tutorial and no tutorial samples).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
Privacy ∼(1—sid)			0.4324701		
+tutorial	1	7.1397	0.4324776	0.0000075	0.0075
+power	6	4.5872	0.4330695	0.0005919	0.2046
+application	9	404.8037	0.4829461	0.0498766	<.0001
+body position	12	1.0868	0.4830739	0.0001278	0.7803
+display	18	37.8901	0.4875364	0.0044625	<.0001
+data synchronization	19	2.1860	0.4877914	0.000255	0.1393
+data storage	20	93.0265	0.4985205	0.0107291	<.0001

Table A13. Effect of scenario parameters on the effort and attention users expect the device to require (both tutorial and no tutorial samples).

Model	df	Chi-squared	R-squared	Δ R-squared	*p* Value
effort/attention ∼(1—sid)			0.2900129		
+tutorial	1	0.93821	0.2900129	0	0.3327
+power	3	206.62788	0.3226086	0.0325986	<.0001
+application	3	4.82015	0.3233509	0.0007423	0.1855
+body position	3	22.64370	0.3268272	0.0034763	<.0001
+display	6	252.32073	0.3642018	0.0373746	<.0001
+data synchronization	1	5.27655	0.3649648	0.000763	0.0216
+data storage	1	0.23569	0.3649986	0.0000338	0.6273
Interactions					
+power:data synchronization	3	10.41105	0.3666445	0.0016459	0.0154

Table A14. Effect of scenario parameters on participants' tendency to upgrade the wearable within or after three years (both tutorial and no tutorial samples).

Model	df	Chi.squared	R-squared	Δ R-squared	*p* Value
Upgrade ∼(1—sid)			0.6218575		
+tutorial	1	3.0570	0.6222476	0.0003901	0.08039
+power	3	32.1494	0.6284470	0.0065895	<.0001
+application	3	2.9080	0.6290060	0.000559	0.40603
+body position	3	4.9756	0.6299967	0.0009907	0.17359
+display	6	3.0317	0.6306474	0.0006507	0.80485
+data synchronization	1	1.2712	0.6308773	0.0002299	0.25955
+data storage	1	4.6252	0.6319010	0.0010237	0.03151

A9. Upgrade intention

Participants were asked how often they would upgrade the presented device, with the options [once every year, once every 2 years, once every 3 years, once every 4-5 years, once every 6-10 years, I'd plan to keep this device for more than a decade] . We transformed this variable into a binary variable by dividing the six options into a binary decision to upgrade within 3 years (0) or after more than 3 years of use (1). In both groups, the device's power source and where it stores the data have significant effect, explaining 0.65% and 0.10% respectively of the variance in upgrading decision (see Table A14). We did not find any significant interaction effect between the device power source and other scenario parameters on the users' decision to upgrade their devices within vs. after three years.