From Smartwatches to Research Tools: Unlocking the Potential of Modern Health Monitoring Technology

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Abstract A broad range of sensing technologies, devices, and platforms allow interested users or physicians to observe various health-related aspects of the user's health. This chapter discusses what modern devices can measure and how users can access and interpret recorded data. Many commercially available devices are capable of measuring data such as heart rate and heart rate variability, sleep cycles, walking steadiness, or electrocardiograms using only a smartwatch and a smartphone. In this chapter, we provide a brief overview these technologies and tools, how they are used for research purposes and highlight potential avenues for future work and upcoming challenges.

Keywords Sensors · User-generated data · Health · Consumer technologies · Health data · Medical devices

Abbreviations

AI	Artificial intelligence
API	Application programming interface
CGM	Continuous glucose monitoring
ECG	Electrocardiography

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HCI	Human-computer interaction
IMU	Inertial measurement unit
PPG	Photoplethysmography

1 Introduction

The wide range of available sensing technologies, devices, and platforms presents exciting opportunities for digital public health (DiPH). Some solutions have been specifically designed for health applications (e.g., health wristbands), while others are based on off-the-shelf technologies adapted for DiPH applications. Ambient data recordings through our everyday technical devices, such as smartphones or smartwatches, allow for numerous advantages when compared to sporadic diagnostic measurements of the past, for instance, when visiting a doctor. Digital infrastructures allow healthcare and medical professionals and automated services to gain deep insights into their patients' medical history, leading to highly personalized treatment (Cancela et al. 2021). Personal devices offer their users increased insight into and control of health-related issues in their daily lives, enabling them to be more autonomous with regard to their own health, both mentally and physically.

What a suitable technology or platform for DiPH can be is not clearly defined, nor is what it might entail. This chapter will, therefore, offer an overview of available technology and a few exemplary interfaces to access the collected data and their use in research. The wide availability of technologies including the high pace at which they are developed and introduced to potential users, poses the risk that this chapter will be quickly outdated. To maintain relevance, we take a human-centered perspective focusing on the current state-of-the-art while employing examples that can be generalized. This chapter begins by explaining how data are collected in the first place, highlighting common technologies used for recording health-related data and describe how these data are stored and processed. We will also provide a general overview of the benefits when users are empowered to self-monitor aspects of their health. Here, an important factor is the availability and accessibility of mobile applications to translate the data into an easily comprehensible format using natural language and assisting visuals. As these data further open avenues for interesting research fields, we will outline current work building on related technologies to illuminate potential future impacts.

2 Sensors

Today, health data and health conditions can be easily monitored by a plethora of sensors that are integrated into the devices that serve as our daily companions. Smartwatches, for instance, are able to detect and count steps taken throughout the day, calculate heart rate and its variability, and even track our sleep quality.

Looking closer at our heart rate, one of the most commonly recorded health data, there are two ways to measure it. The first option is to record the heart's electrical activity through electrocardiography (ECG) (Feather et al. 2020). The device detects small electrical pulses and changes during the cardiac cycle via electrodes placed on a person's skin. ECGs are commonly used in professional medical devices but can also be found in chest straps at an affordable price. Chest straps are often used in professional sports and can send data through Bluetooth to another device (Lapinski et al. 2009). However, these chest straps are sometimes uncomfortable to wear and can cause skin abrasion. Furthermore, the use of ECGs can also be found in some smartwatches. With the benefit of being ubiquitous compared to chest traps, the accuracy of smartwatches is worse than other professional devices.

The second method of measuring heart rate is by using the process of photoplethysmography (PPG). This measurement method uses optical sensors built into smartwatches or other wearable devices. By sending light from small LEDs through the skin, the sensor detects the volume of blood flowing through the body. This information is then used to derive a heart rate (Castaneda et al. 2018). Unfortunately, optical sensors are prone to optical noise. Since the sensor sends light through the skin, dirt, water, motion, and other disruptive factors can lower the accuracy of the calculated heart rate throughout the measuring process Singh et al. (2018). Conclusively, PPGs have been shown to be less exact compared to ECGs (Singh et al. 2018). However, some smartwatches are able to detect the heart rate with a 96% accuracy compared to ECGs (Pasadyn et al. 2019).

Next to measuring the heart rate, most smartwatches are also able to calculate the heart rate variability. This value is defined by the time between two heartbeats. Heart rate variability is a value that describes how adaptable the body is in a certain situation to either mental or physical stress. The higher the heart rate variability of the person, the more variance the time intervals between two heartbeats have. Therefore, if stress occurs, the body is able to react to that stress by increasing the heart rate and getting more oxygen sent through our blood into our body to get more energy for that situation. A low heart rate variability correlates to higher mortality, being easily exhausted, and having decreased cognition (Dekker et al. 2000; Shaffer and Venner 2013). The heart rate variability also reflects how recovered an athlete is (Makivić et al. 2013). Also, a sudden lower heart rate variability indicate a high amount of stress which increases the chances of getting sick (Shaffer and Ginsberg 2017).

Another sensor combination commonly used in smartwatches or smartphones is an inertial measurement unit (IMU). An IMU consists of a three-axis accelerometer (measuring acceleration), a three-axis gyroscope (measuring rotation), and a three-axis magnetometer (measuring magnetic fields). Initially used in ships or airplanes for navigation, these units can detect specific motion patterns. Especially in combination with GPS, IMUs can detect steps taken during the day, the speed of running, or the distance walked. IMUs have also been shown to detect exercise execution in athletes. Furthermore, IMUs are also used in systems for fall detection for older adults. Cameras can also be used for motion detection. Similar to IMUs, high-resolution cameras are built into modern smartphones. With the help of software libraries like OpenCV,[1] skeletal movement can be derived and used for further motion analysis.

Sensors can also be used to help people cope with chronic health conditions like diabetes. Through continuous glucose monitoring (CGM), affected persons can monitor their insulin level and react to it accordingly. CGM can be done with either real-time-CGM (rtCGM) or intermittent scanning CGM (iscCGM). rtCGM systems have three parts: a sensor, a transmitter, and a receiver. The sensor is either placed directly under the skin of the arm by professional medical staff or on the skin of the belly. The sensors measure the glucose level in the tissue fluid every five minutes and send the data to the receiver, which can display all the information. If there is a risk of hyperglycemia or hypoglycemia, the receiver triggers an acoustic or vibration alarm so that countermeasures can be taken.

iscCGM systems consist of just a sensor and an app. The sensor is placed at the back of the upper arm. Compared to rtCGM systems, the glucose level is not sent every 5 min to the app but has to be scanned by the user. However, like the rtCGM systems, an alarm is triggered if glucose levels are too high or too low. To stop the alarm, the user must scan the sensor and let the application read out the glucose levels.

This only describes a few possibilities for using sensors in lightweight mobile devices. There are numerous other sensors to scan for temperature, environmental data, like pollution or weather conditions, and more. They offer a vast spectrum of patient and context-specific data that can help us cope with everyday health issues and chronic diseases, monitor daily routines, and help us evaluate our fitness and health levels. In most applications, these sensor data are incorporated into platforms that aggregate information and provide insights gathered by the sensors and summarize the current health status of an individual. Examples of how these platforms work and can be divided into categories are presented in the next section.

3 From Sensor Data to Usable Data

The abundance of sensors available on the market that are already built into commercially available wearable devices, such as smartwatches, fitness trackers, or medical devices, allow for extensive data recording for an interested user, e.g., health-conscious persons or athletes, or patients in a medical context. Another user group is researchers, who can use the devices to easily record additional physiological data for a specific context or work on expanding the potential of the wearable devices (see Sect. 4 for examples). In the medical context, Lu et al. (2020) categorized the application of wearables into four areas: health and safety monitoring, chronic disease management, disease diagnosis and treatment, and rehabilitation. Although, based on the description given by them (based on the reviewed

[1] https://opencv.org/, accessed 12th July 2023.

literature), the use of an interested person would come within the category "health and safety monitoring" as it generally describes the everyday application areas of wearable devices, especially more complex devices like smartwatches. In the following paragraphs, we will describe how users can access their data and present a few exemplary applications aggregating the recorded data. Furthermore, as not all health data are recorded by wearables equipped with sensors, we briefly highlight the usage of user-generated data and provide an application example in the context of "chronic disease management." Lastly, we briefly discuss potential problems with the current data presentation.

One challenge originating from the vast amount of data is to provide the information in a usable and understandable way to the owners of these devices. Most modern wearables have the tracking hardware conveniently integrated, and they either have a pre-installed interface, such as the Apple Health App (see Fig. 1) or apps or web interfaces that are available to view the data. The Apple Health App aggregates data from two central sources: the iPhone and the Apple watch, a smartwatch integrated with a fitness tracker. Additionally, other apps can feed their data into the

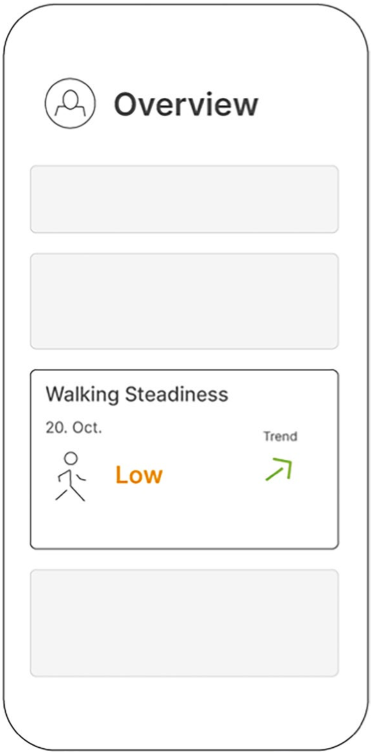

Fig. 1 An overview of the current walking steadiness of a person. (Source: Own figure)

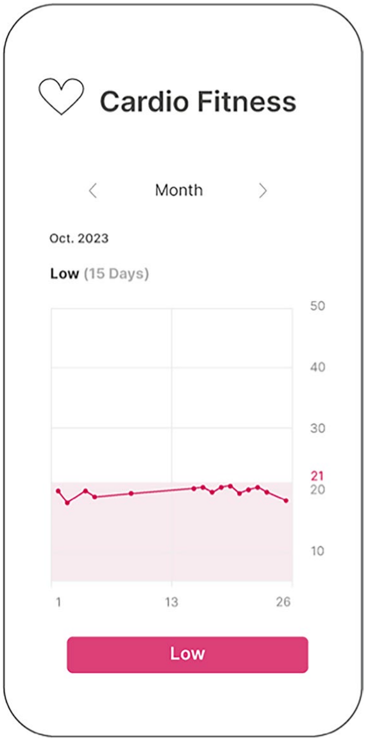

Fig. 2 An overview of the Cardio Fitness level of a person. (Source: Own figure)

Health App, such as Fitbit,[2] Komoot,[3] Nike training,[4] One Drop Diabetes Management,[5] and many more. Thus, the Health App provides an overview of various health-related data—mainly focusing on health and safety monitoring but also providing limited chronic disease management. Additionally, it already provides an interpretation, e.g., how the cardio fitness level is based on the information available (see Fig. 2). While these data are presented to the user on a mobile device, other brands also provide web interfaces to view the data (cf. Fitbit Dashboard Fig. 3).

Where these applications primarily target the general public and athletes, there are also apps and measuring devices certified as medical devices. They visualize the data for their users allowing doctors to monitor their patients better. One example would be KardiaPro[6] device that can record an ECG and relay the data to the attending cardiologist. In Germany, doctors can even prescribe apps and medical devices to support tracking certain diseases. As diabetes is a widespread illness, monitoring one's blood sugar values is essential and of interest to the attending physician. Apps

[2] https://www.fitbit.com/global/us/home, accessed 12th July 2023.

[3] https://www.komoot.com/, accessed 12th July 2023.

[4] https://www.nike.com/de/ntc-app, accessed 12th July 2023.

[5] https://onedrop.today/, accessed 12th July 2023.

[6] https://clinicians.alivecor.com/, accessed 12th July 2023.

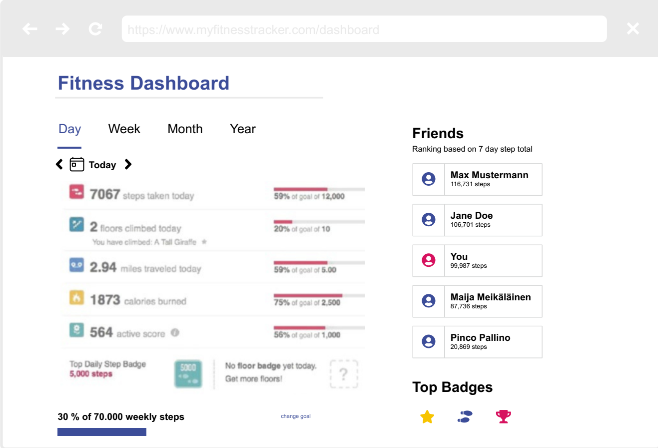

Fig. 3 An exemplary dashboard giving an overview of aggregated data. (Source: Own figure)

like FreeStyle Libre[7] are designed for people with diabetes who wear a sensor measuring their blood sugar values. The app provides real-time feedback on the condition, and the user can also share this information externally.

All the presented applications are similar in that they rely on data measured by dedicated sensors and hardware, e.g., a fitness tracker, a blood sugar sensor, or an ECG-capable device. For data derived from the sensors listed in Sect. 2, the processing and interpretation of the data are especially critical, as the raw values measured are often very noisy and rarely readable to an untrained eye much the same as a standard ECG. It is particularly helpful for users to see their data put into context; for example, see the sketch based on commercially available tools in Fig. 1, which tells the user their walking steadiness is okay. A similar perspective is given in the sketch in Fig. 2, which shows a more raw value, but the interpretation is provided on the bottom in the form of the text stating "low". Most often, the information is presented in a graph that allows the user to compare their performance and their individual goals over a period of a week or month, and even compared to others, as seen in Fig. 3.

Apps can also provide an overview of health-related data entered by the users and not automatically tracked by specific hardware. Several apps visualize and interpret data that the user consciously created. One commonly known example is digital food diaries to keep an overview of the number of calories, fiber, nutrients, etc., digested (e.g., MyFitnessPal[8]) or to examine the relationship between food and health issues (e.g., Nutrimizer[9]). But diseases can also be tracked using digital means. One example is the DMKG-App (DMKG = Deutsche Migräne- und

[7] https://www.freestylelibre.de/produkte/freestylelibre-apps.html, accessed 12th July 2023.

[8] https://www.myfitnesspal.com/, accessed 12th July 2023.

[9] https://nutrimizer-app.com/Nutrimizer/, accessed 12th July 2023.

Kopfschmerzgesellschaft, in English: German Migraine and Headache Society), which is accompanied by a web interface that allows for entering further information that can be shared with the attending neurologist. The app prompts the users daily to enter data about their day—whether they had a migraine or headache. If they experienced either, the app asks if and what medication they took and if additional symptoms like dizziness or a migraine aura appeared. The system then provides an overview of the data, for example, the average duration of the headache (see Fig. 4 top graph) and the reported pain level (see Fig. 4 bottom graph). It is an excellent example of how modern health technology can support chronic disease management by facilitating documentation of disease activity by the patient and sharing of this documentation with the treating physician.

Overall, one of the main features of these applications is to present aggregated data—either automatically tracked by dedicated devices or manually entered by the

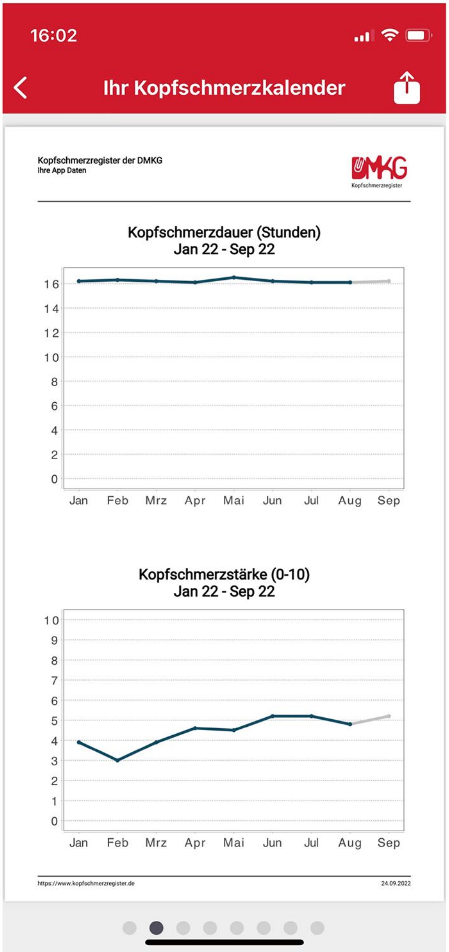

Fig. 4 One overview of user-entered data for a migraine and headache tracking app. Top graph: average duration of the headache; bottom graph: the reported pain level. (Source: DMKG-App, German Migraine and Headache Society)

user—understandable for users without medical training. Often the designers rely on some form of graphs that might be enriched with numbers. Based on the interface snippets of this section, the designers seemed to be aware of color blindness aspects, as they avoided obvious red-green contrasts to make it readable for everyone, including those with the most common forms of color blindness. Nevertheless, as the data are presented primarily in a visually appealing way, the question of accessibility arises. Most designs are "premised on implicit assumptions about the reader's sensory, cognitive, and motor abilities" (Marriott et al. 2021). Therefore, everyone without these abilities does not have access to the benefits of data visualization and have only limited access to the underlying information. There are diverse solutions that allow blind or visually impaired people to access the data, such as alt texts, sonification, or tactile graphics (Marriott et al. 2021). But with continuously generated graphs based on the latest input, these solutions do not work. There is some rudimentary support from the accessibility features of different devices. For example, Apple has a "VoiceOver" feature[10] that reads out the chosen data point when the user selects specific parts on the graph. But this is far away from creating access to the benefits of visualization. Therefore, we look forward to the technical advancements of the future, making the data accessible to everyone in an easily usable, insightful, and unrestricted way and also providing a well-designed user experience for everyone.

4 Smart Devices as Research Tools

Besides the various opportunities for end consumers mentioned in the previous section, another field of application for smart devices is becoming increasingly important: research. One prominent use case is equipping test persons of drug trials with wearables measuring physiological data both to achieve higher safety through continuous monitoring and to get deeper insights into the medication's effects (Izmailova et al. 2017). Additionally, there are plenty of examples to be found in psychological research, such as Triantafillou et al. (2019), who used smartphone-based ecological momentary assessments[11] and activity recognition provided by the respective Android API[12] in order to explore the relationship between sleep quality and mood. In the context of a study examining the physical and mental health of college students during the COVID-19 pandemic, Gilley et al. (2022) provided their participants with Fitbit[13] wristbands hoping to get additional information from other fitness indicators, e.g., based on daily steps. Another example is the study of Faust et al.

[10] https://support.apple.com/guide/iphone/turn-on-and-practice-voiceover-iph3e2e415f/ios, accessed 12th July 2023.

[11] https://www.gov.uk/guidance/ecological-momentary-assessment, accessed 12th July 2023.

[12] https://developer.android.com/guide/topics/location/transitions, accessed 12th July 2023.

[13] https://www.fitbit.com/global/eu/home, accessed 12th July 2023.

(2021) whose objective "was to quantify how an individual's physical health changes in response to negative life events by testing for deviations in their physiological and behavioral state (PB State)." The PB State comprised resting heart rate, physical activity, and sleep duration measured by Garmin[14] Vivosmart-3. Using fitness trackers instead of users self-reporting data through surveys was reasoned by recall bias. In general, other benefits of using consumer devices as research instruments might be lower costs and effort both for participants and researchers (Izmailova et al. 2017), unexpected insights resulting in new hypotheses (Chromik et al. 2022) and undistorted observations of participants in their everyday lives (Chromik et al. 2022). Nevertheless, several challenges remain, such as data security and privacy or lack of competence in handling the vast amounts of generated data on the researchers'part (Izmailova et al. 2017).

5 Future Directions and Chances

The previous sections presented a broad range of application scenarios for health monitoring technology. However, there is still great potential to be fulfilled in the future. In our view, both end consumers and researchers will profit from three particularly noteworthy trends:

1. **Higher-level information thanks to Artificial Intelligence (AI):** Going beyond the use of devices as a tool for recording mere physiological data, researchers are trying to feed more and more sophisticated AI models with the help of health monitoring technology: For example, the approach of wearable-based detection of COVID-19 infections is—among other research groups all over the world—pursued by Risch et al. (2022) with the name "COVI-GAPP." A cohort from Lichtenstein was equipped with Ava fertility trackers and asked to wear them at night so that respiratory rate, heart rate, heart rate variability, skin temperature, and skin perfusion measurements could be performed. Besides this, the participants were tested for COVID-19 on fixed dates as well as in case of symptoms within the duration of the study. The collected data were used to train a Recurrent Neural Network to predict a COVID-19 infection during the presymptomatic phase. The project's overall aim is to give people an easily accessible tool that informs about a possible COVID-19 infection at an early stage and thus limits the risk of virus spread. Furthermore, wearable-generated data are not only useful concerning the analysis of a person's physical condition but also in terms of health-related behavior. For instance, Kappattanavr et al. (2022) examined the performance of a random forest classifier trained on wrist motion data to recognize food intake gestures. The researchers addressed an application scenario where people get automatic smartphone notifications directly after meals reminding them to keep their food

[14] https://www.garmin.com/en-US/, accessed 12th July 2023.

diaries. Their idea was to ensure adherence to a healthy diet, which might prevent the onset of diabetes in the long term. As these technologies require significant amounts of user-generated health data to achieve high performance, privacy issues arise. One approach is Federated Learning[15] which provides that model training is performed on the user's device itself so that only model updates are sent to a central server coordinating the training process. However, there are still some pitfalls regarding data security, e.g., attackers trying to reconstruct the original data from the updates. In order to defend against these "reconstruction attacks"[16] a possible solution could be utilizing Differential Privacy[17] i.e., adding a certain amount of noise to the data before sending it to the central server. Islam et al. (2022) demonstrated this procedure using the example of model training on genomic data.

2. **Further and newly developed sensor technology:** As existing sensors are improved, and new types of sensors are developed, the number of possibilities in terms of health-related applications for (wearable) devices also increases. One exciting field is that of flexible and/or textile sensors. They promise to be much more comfortable compared to common sensors made from rigid materials, offer improved sensitivity due to better fit onto the skin (Zazoum et al. 2022), and allow the performance of new kinds of measurements, e.g., bending movements of the trunk (Patiño et al. 2020). However, several issues regarding, for example, energy supply and efficiency, washability, and regulatory framework for safety (Tat et al. 2022) still need to be solved.
3. **Embedding in larger systems:** Although, as discussed in (1), even a single fitness tracker may address many health challenges, combining different sensor technologies or integrating them into larger systems allows to create value for health in more complex contexts. An example of this might be medical emergencies. Haghi et al. (2021) presented a communication platform for information exchange between an alerting system (e.g., smart home, wearable), a responding system (e.g., ambulance), and curing system (e.g., hospital). A scenario could be the fall of a person in their home detected by a wearable and/or smart home device: n available ambulance gets both alerted and provided with detailed information (e.g., the person's exact position in the building and his medical condition based on previous illnesses and current physiological data) automatically. Finally, the person is brought to a suitable hospital in the surrounding area (Paul L. Reichertz Institute 2020).

[15] https://en.wikipedia.org/wiki/Federated_learning, accessed 12th July 2023.

[16] https://en.wikipedia.org/wiki/Reconstruction_attack, accessed 12th July 2023.

[17] https://de.wikipedia.org/wiki/Differential_Privacy, accessed 12th July 2023.

6 Discussion and Conclusion

Digital technology for public health is a trend that is here to stay. As outlined in this chapter, we already have access to a great variety of sensors, applications, and devices that are established on the market and used by a broad user population.

The benefits of these techniques range from individual health tracking and feedback for individual adaptations of, for instance, user behavior or medication to epidemiologic health research with large cohorts of users. Yet, many issues need to be addressed. This chapter has discussed some of them, along with current solutions and future developments in this chapter. Along the pipeline from data acquisition to aggregation and presentation are various challenges that need engineering, AI, and HCI solutions.

On the one hand, these technologies bear the potential to increase public health significantly on an individual and cohort level. They can help identify/diagnose problems, provide long-term data, give feedback, and support prevention, cure, and rehabilitation for many current health threats such as obesity, diabetes, mental health, infectious diseases, and more.

But next to this bright future, there are still big challenges that must be solved. In particular, data privacy and security issues become susceptible to exploitation when large amounts of highly sensitive health data are collected from users over long periods of time and aggregated on individual mobile or centralized servers.

More technical issues arise from the multi-device and multi-platform infrastructure that is also extremely dynamic. If health data are to be collected reliably over a long time span, compatibility issues need to be resolved.

For future development, however, the focus must not be distracted from technical questions but should be guided by a human-centered approach, as the goal of all these developments should be a sustainable improvement of the users' health.

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