Investigating User Perceptions Towards Wearable Mobile Electromyography

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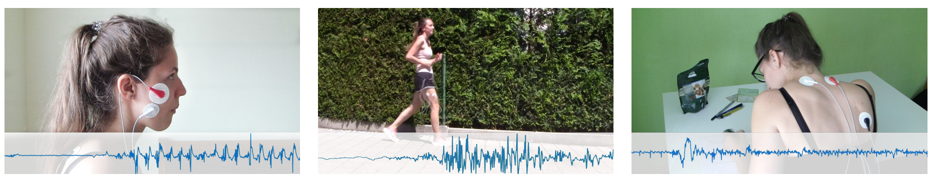


(a) Chewing (b) Gait (c) Stress

Fig. 1. We conducted a user study (N=36), investigating users' perceptions of wearable EMG applications. Participants (A) tried out our EMG prototype and (B) watched videos showing several EMG use cases, evolving around (a) Chewing, (b) Gait, and (c) Stress.

Abstract. Wearables capture physiological user data, enabling novel user interfaces that can identify users, adapt to the user state, and contribute to the quantified self. At the same time, little is known about users' perception of this new technology. In this paper, we present findings from a user study (N=36) in which participants used an electromyography (EMG) wearable and a visualization of data collected from EMG wearables. We found that participants are highly unaware of what EMG data can reveal about them. Allowing them to explore their physiological data makes them more reluctant to share this data. We conclude with deriving guidelines, to help designers of physiological data-based user interfaces to (a) protect users' privacy, (b) better inform them, and (c) ultimately support the uptake of this technology.

Keywords: wearable devices · user perceptions · electromyography · privacy

1 Introduction

An increasing number of physiological sensors, which can be embedded in wearable devices, are surrounding us today. These allow users' physical, physiological, and even cognitive state to be constantly monitored [64]. With advances in computational power, storage capacity, and network connectivity, large amounts of data gathered through wearable devices can be processed and stored in the cloud. This development allows researchers and commercial applications to build intelligent user interfaces based on physiological data [36, 72]. Furthermore, this also provides insights about users' health and well-being through commercial apps like Google Fit or Fitbit as well as research applications, e.g., [11, 39, 77].

A wide variety of physiological sensors are making their way into consumer electronics, for example, the Apple Watch Series 4 onwards contains an electrocardiogram (ECG) sensor[3]. In this work, we are focusing on electromyography (EMG) as one such sensor. EMG sensors and data are particularly interesting from a research perspective because they can be easily deployed over a long period of time (i.e., several weeks) and on various parts of the body. EMG refers to electrical signals created by the muscles. Sensing the electrical signals allows to track muscle "activity", such as *contraction* or *relaxation* [59]. The signal strongly depends on the anatomical and physiological properties of a muscle and thus can, for instance, serve as a biometric feature [38]. On a higher abstraction level, posture or muscle contraction-specific information can be derived based on an EMG signal and then be classified into control commands using a neuronal network [30] or feature-based classifier [3]. For input purposes even commercial products are available, for example, the Myo wristband enabling advanced gesture input [53]. Moreover, while other sensors, such as ECG, can recognise users being active, EMG data can identify the respective activity (e.g., stepping stairs). As a consequence, EMG can provide more detailed insights into the human's health. For example, research demonstrated how EMG data can be used to gain insights about users' chewing [7, 15], gait [13, 19], and stress [73] behaviour (cf. Figure 1). At the same time, the underlying data can be used to derive further information, such as users' health and well-being. Thus, this type of sensitive data has to be treated with care [14, 45] – in particular, as Rocher et al. [60] has shown that artificial intelligence (AI) can deanonymize whole data sets.

These developments create a need to investigate users' perception towards collecting, processing and storing physiological data. At the same time, researchers and practitioners should be aware of the risks and users' perception when designing systems involving physiological signals [37]. While users are aware of privacy concerns regarding other sensor data (e.g. GPS [2]), their awareness of risks regarding physiological data, in particular EMG data, is not well understood yet.

To close this gap, we investigate to which degree users are aware of the potential privacy risks posed by EMG data. In a study, we evaluated (1) participants' sharing behaviour in general and for physiological data based on EMG in particular and (2) assessed participants' opinions towards the privacy of EMG data. We found that participants changed their willingness to share EMG data over the course of the study as they are getting a better understanding of what risks the data entails. Furthermore, we derive a set of guidelines for designers of EMG-based user interfaces, helping them to protect users' privacy, better inform them about the involved risks, and ultimately support the uptake of EMG technology.

All sources last accessed June 8, 2021

[3] https://support.apple.com/en-us/HT208955

2 Related Work

To understand users' perception of wearable EMG devices, we first investigate what EMG can reveal about users. Thus, we review work on EMG and describe use cases. We then present state-of-the-art metrics to assess users' perception on personal data and their privacy. Finally, as sensor data is prone to constitute uncertainty, we also review visualization techniques for uncertainty.

2.1 EMG-based User Interfaces

Related work shows that EMG and physiological signals provide valuable opportunities for novel user interfaces. As measuring electrical signals from muscle activity offers a new modality for intuitive input, a wide range of applications have emerged. The most prominent area of EMG-based user interfaces is using the signals to classify hand gestures [36, 48]. Application areas include scenarios where the hands are occupied, e.g., to support safety during cycling [40], smartwatch interaction [41], or interactive storytelling [23]. In addition, EMG is also used to recognize sign language [1], in human robot collaboration tasks [72], and even fine-grained detection like the pressure applied by a finger [4]. While these prior works placed the EMG electrodes mainly on the arm, a smaller number of research also investigated other muscles. Here, Huang et al. [33] for instance, used facial EMG to help people with disabilities control a mouse cursor. Additionally, Gibert et al. [22] also applied EMG to the face with the goal of providing better facial mimics for virtual reality (VR) avatars.

EMG has also been explored to provide better insights about health and well-being using wearable devices. EMG electrodes on the legs allow motion patterns to be identified, e.g., for distinguishing running from walking [13] or to calculate speed from users' gait [19]. EMG measured at the trapezius muscle (i.e., in the neck) can serve as a stress detector [73]. In daily life self-tracking situations, EMG could support eating reports as it allows detecting chewing [7, 15].

From this we learn that EMG sensors can serve a variety of purposes as more detailed activity information – as compared to other sensors – can be revealed. Thus, a large variety of application areas exists for EMG data and we will likely see many novel user interfaces and interaction techniques in the future.

2.2 User Perception & Privacy

Privacy is a challenge in ubiquitous computing, due to the properties of novel devices: ubiquity, invisibility, sensing, and memory amplification [42]. Also, collected data can generate knowledge about users which is available to everyone [50, 68]. Calo [12] states "privacy harm as a unique type of injury" [12]. Thus, privacy protection is crucial.

Wearables, one type of ubiquitous devices, are increasingly present in users' daily lives, for example, fitness trackers, or smartwatches. They raise particular privacy concerns as they are continuously tracking sensitive user data (for example, health related). Motti and Cane [49] found several factors influencing users' privacy concerns with wearable devices. They highlight that these concerns depend on the type of device, the nature of data, and on the ability to share or disclose the data. Health tracking is often combined with online sharing, which raises privacy issues [58]. Moreover, Wilkowska and Ziefle [74] highlight privacy aspects to be considered to allow for adoption of medical assistive technologies. At the same time, Rahman et al. [58] showed that fitness trackers, such as Fitbit, are relatively easy to attack.

Privacy issues often arise when health data is being shared. Puussaar et al. [57] show that users' willingness to share fine-grained data is redacted. Gorm and Shklovski [25] showed that, in the workplace, participants got more reluctant to share their counts over time. With regards to mobile app usage, users may perceive privacy being violated in "creepy" ways [67].

To address privacy issues with ubiquitous devices, Langheinrich [42] suggests to preserve privacy by design, for example, by informing subjects about data collection, receiving explicit consent, or by keeping anonymity of tracked subjects. Here, Schaub et al. [63] propose a design space for effectively informing users about a system's data practices. Hoyle et al. [32] suggest in-situ control of privacy for wearable lifelogging cameras. Perez and Zeadally [55] propose mechanisms to control data collection in wearables for privacy protection. They argue that anonymization should be applied even to aggregated data. Lau et al. [43] integrate privacy controls for smart speakers, such as Amazon Alexa. Since the main user concern is potential surveillance via smart speakers, they suggest commands like "Alexa, stop listening" [43]. Paul and Irvine [54] highlight privacy issues when using health monitoring wearables, namely data ownership, classification, and storage.

Related work shows that privacy is a challenge in ubiquitous computing, in particular, when obtaining and potentially sharing users' physiological health state. However, users' perception towards physiological data collection and sharing has not been investigated in depth so far, which is at the focus of our work.

2.3 Uncertainity Visualization in Sensor Data

In data visualization, communicating uncertainty [52] is important. This is particularly true for aggregated data, since insights might get lost due to the aggregation, such as weather forecasts [24, 27], public transport prediction [35], car range prediction [34], or gene exploration [66]. Moreover, visualizing uncertainty supports making informed decisions [28, 62].

Error bars are the most common tool to communicate uncertainty [17, 29]. Additionally, uncertainty can be presented by changing the visual properties, e.g., blur [26, 29], color, or transparency [16]. To highlight specific data and uncertainty, more complex visual components can be added to the visualization [8, 10], such as, for instance, annotations [18]. Results indicate that error bars are suitable for tasks without probability values. We conclude that when visually presenting data, it is important to also represent uncertainty in the visualization to support sense-making. In our work, we use uncertainity visualizations in the form of error bars to support EMG data discovery.

3 Hypotheses

EMG sensors are easy to deploy and the data obtained from EMG sensors can not only be used for interaction, but also reveal detailed information about users' activities and well-being. Thus, it is important to foster a better understanding and awareness of personal sensor data. Our research is guided by the following hypotheses:

H1 **Users are concerned about sharing personal EMG data.** Motti and Caine [49] show that wearables are generally of concern for users. As EMG has a rich potential to uncover daily routines, habits, and health status, we hypothesize that users are concerned about recording/sharing their personal EMG data.

H2 **Providing users an understanding of EMG sensor data will change their sharing habits and privacy attitude.** Puussaar et al. [57] show that users' willingness to share fine-grained data is low. We hypothesize demonstrating the richness of EMG data will reduce users' willingness for sharing and recording.

H3 **The degree of detail of data visualization influences participants' opinion on recording and sharing sensor data.** Greis et al. [28] showed that presenting uncertainty information improved users' ability to judge the data. We hypothesize that presenting visualizations (of aggregated data) will result in greater willingness to share, even if content providers may keep fine-grain data.

4 Study

To test our hypotheses we conducted a mixed methods user study with 36 participants. We asked participants (Part A) to try a music player prototype which they could control using an EMG device, and (Part B) showed them three videos of activities and the corresponding real EMG data (i.e. chew, gait, and stress – see Figure 1), and aggregated visualization dashboards.

In Part A, we used prototyping as a research method [61] to convey the experience of using an EMG device. Additionally, we presented users their own real-time EMG feedback. In Part B, we used a low-fidelity prototype [61] of an interactive dashboard with pre-recorded EMG data from three different scenarios and supplementary videos showcasing the scenarios. Figure 4 illustrates the two parts of our study and in the following we describe in detail our study design. This research method of presenting videos or images to ask about users' opinions is well established and common in human-computer interaction (HCI) [65, 71].

4.1 Part A: EMG Music Player Prototype

We implemented a simple EMG application where the user can like or dislike music, using an EMG sensor. We used the Spotify web API[4]. We implemented a genre selection feature as well as play and pause using the mouse. Each song played for 15 seconds until moving to the next song. Users had the possibility to like or dislike a song by using the thumbs up or down gesture while the system detected the gesture with three dry, passive, non-invasive electrodes placed on the user's forearm (see Figure 2). The system provided feedback for every EMG like/dislike. Additionally, the users were shown their own EMG signal. Note that the music player was solely meant to showcase what EMG is and how it works in practice, rather than being a privacy-sensitive use case.

[4] https://developer.spotify.com/documentation/web-api/

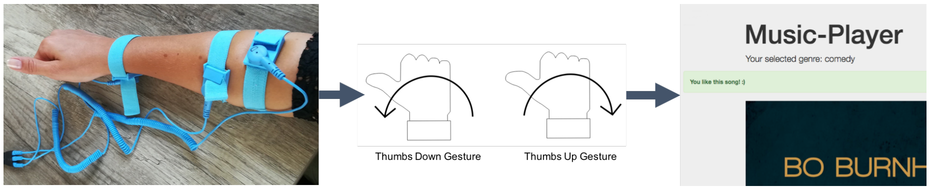


Fig. 2. EMG Showcase Music Player: Dry, passive, non-invasive electrodes were mounted on the participants' forearm to receive the thumbs up and down metaphor for like or dislike.

4.2 Part B: EMG Use Case Visualizations

In Part B, we follow a mixed-model design with two independent variables: UseCase, and Detail. While UseCase was a within-subjects variable with three levels (*Chew*, *Gait*, *Stress*), Detail was a between-subjects variable with two levels (*Low*, *High*). We counter-balanced UseCase within Detail using a Latin square design [75].

We chose three UseCases, to show participants what information can be extracted from EMG data using video clips which we carefully created in a neutral way (i.e., we generated the videos without highlights, zoom shots, or other special effects to keep them simple, cf. Figure 1).

(a) *Chewing*: As a more unusual use case, we choose detecting chewing movements from EMG (as shown by Blechert et al. [7]). This is closely related to users' routines, eating behaviour and health state (referring to, for example, eating disorders). In this video, we showed scenes of people eating soft food and hard food as well as drinking water.

(b) *Gait*: Related work showed that gait patterns can be identified from EMG signals [13, 19]. In addition, Google SmartLock[5] tracks gait features for on body detection. Moreover, many users keep track of their gait. Thus we assume gait to be an important application case for users of tracking technologies. In this video we showed a short sequence of gait scenes, including walking, running, and stepping stairs.

(c) *Stress*: Tracking productivity is a common use case. At the same time, high workload may result in stress situations for users. Stress can be detected using EMG [73]. The actor of this video was in a relaxed situation first, while showing a stressful exam situation afterwards.

We created dashboards to visualize mock EMG data per UseCase. The dashboards were designed similar to other dashboards people use to track their fitness, health state, or analyze their behaviour, e.g., Endomondo[6], Google Fit[7], Apple Health[8], or RunScribe[9]. We evaluated two levels of Detail (i.e., *Low* and *High*, cf. Figure 3),

[5] https://support.google.com/android/answer/9075927
[6] https://www.endomondo.com/?language=EN
[7] https://www.google.com/fit/
[8] https://www.apple.com/lae/ios/health/
[9] https://runscribe.com/

(a) Low level of DETAIL (b) High level of DETAIL

Fig. 3. EMG Dashboard: We provided insights into fictive EMG data to our USECASES. Participants were randomly assigned to one group of DETAIL: a) *Low* or b) *High*.

differing in the level of *aggregation*: *Low* presents one bar chart of aggregated data (Figure 3a), while *High* presents multiple charts and single data values (Figure 3b). For instance, for the USECASE *Gait*, the dashboard of *low* detail shows the total and average number of steps, distance and duration per day or per week. The *high* level of detail dashboard shows single values for steps, distance and duration as well as information on speed, direction, and movement per foot.

4.3 Data Collection

During the study, data was collected by means of questionnaires and interviews (cf. Figure 4), which we describe in detail below.

Introductory Interview. We first conducted a semi-structured interview asking about any use of fitness trackers or other wearables and if so why participants used them. We also asked if they know what electromyography (EMG) is and explained this if necessary. Further questions included: *"What do you think would be the most likely risks associated with wearable devices?"* and *"What do you think, what role does security and privacy play to health monitoring devices in this respect? Do you think it is important and, if so, why?"*

Sharing Behaviour & Privacy Questionnaire. To understand if and how participants generally share personal data (with whom), we designed a questionnaire that synthesizes related work. The questionnaire covered the following topics: social media sharing behaviour [70], how the content type (personal or sensitive, sensational, political, and casual information) influences sharing behaviour [51], the motivation to share [21], participants' opinion of privacy, and their own data [5, 47]. To understand how they generally think about privacy, we included the 10-item IUIPC questionnaire [47] (Table 1, Q4–13).

Intermediate Questionnaire. To investigate whether increased understanding will change users' sharing habits (H2), we presented participants with an intermediate

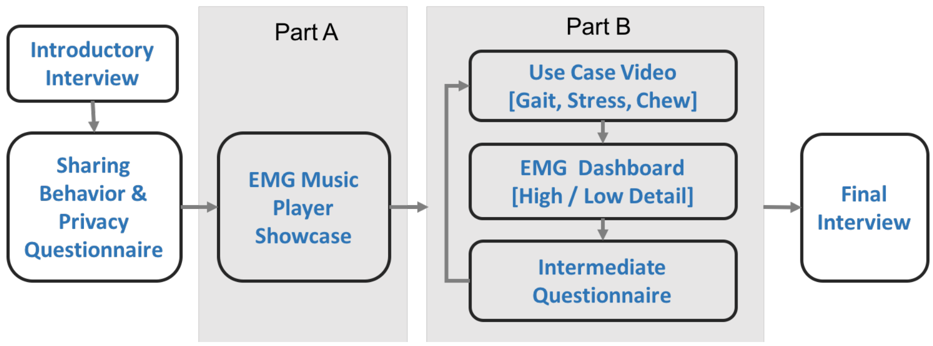


Fig. 4. Study procedure. Part A: EMG prototype. Part B: EMG videos / visualizations.

questionnaire following each UseCase. We included questions about privacy with regards to this particular data. We asked 1) whether or not they would share this data, 2) about the impact of sharing this data without permission, and 3-6) if they would share this EMG data with <*recipient*> (being one of classmates/colleagues — friends — family — public [44]).

Final Interview. We conducted a semi-structured interview on possible EMG use cases, what users learned, and their feelings about EMG recording and sharing.

4.4 Procedure

The study was conducted in a single room at our institute. The session took 45-60 minutes per participant. The detailed procedure was as follows (cf. Figure 4 for an overview):

(1) *Introduction.* We started by welcoming participants, and explaining the purpose of the study. We then asked participants to fill in a consent form, and started with the *introductory interview*. After filling in a demographics questionnaire (including use of social media), we asked participants to fill in the *Sharing Behaviour & Privacy Questionnaire* to understand their behaviour and risk perception prior to the study. We then continued the *introductory interview* as participants by now already thought about possible implications (addressing H1).

(2) *Part A.* Part A started with making all participants familiar with EMG. To close possible knowledge gaps, participants tried our *EMG music player prototype* (around 10-15 minutes). We attached three electrodes to the participants' forearm (Figure 2) and showed participants the thumbs up/down gesture to like or dislike songs. The UI showed the current song and genre and, more importantly, visualized the live EMG signal. The visualization enabled participants to explore their own EMG input.

(3) *Part B.* Afterwards, we continued with Part B in which we presented the three different UseCases to participants in counter-balanced order as *videos* (i.e., participants did not try these themselves). Participants were asked to explore the possible

insights into the data using our *visualization dashboard*. Participants were randomly assigned to one level of DETAIL to investigate H3. Alongside each USECASE, participants were presented a couple of tasks to solve with the visualization as well as the *intermediate questionnaire* (H2). Tasks were similar to: *"On what day and at what time has the stress level the amount of 12%?"* Additionally, we asked the following three questions for each USECASE: *"What do you find out about the person and the course of the day?"*, *"Can you make any statements about this person's lifestyle?"*, and *"What do you learn about daily habits/routines of this person?"*

(4) *Final Interview.* At the end, we conducted the *final interview* with participants.

4.5 Participants

We recruited 36 participants through a university mailing list and social media to take part in the study (24 female, and 12 male). The age range was between 19 and 64 years ($M=28.6$, $SD=9.2$). 22 of our participants stated to be students, 12 were employed, 1 was retired and 1 stated to currently be unemployed. We asked participants about their most used social media. Two participants stated they do not use social media. All other used social media. Here, Facebook was stated most often (18 times), followed by Instagram (11 times), and YouTube (4 times). Twitter and Snapchat were named by one participant each. We reimbursed participants with €10.

Table 1. Q1 to Q3 are modified questions based on Malhotra et al.'s causal model [47]. Additionally, we asked participants the 10-item IUIPC questionnaire [47] (Q4 – Q13). All reported Likert items are on a 7-point scale (1=strongly disagree; 7=strongly agree).

	Question	M	SD
Q1	I have been the victim of what I felt was an improper invasion of privacy.	2.2	1.7
Q2	I am very concerned about the privacy of my data.	4.7	1.9
Q3	I always falsify personal information needed to register with some websites.	2.9	1.8
Q4	It usually bothers me when online companies ask me for personal information.	5.7	1.5
Q5	When online companies ask me for personal information, I sometimes think twice before providing it.	5.9	1.2
Q6	It bothers me to give personal information to so many online companies.	6.1	1.1
Q7	I'm concerned that online companies collect too much personal information.	5.5	1.4
Q8	Your online privacy is really a matter of your right to exercise control and autonomy over decisions about how your information is collected, used, and shared.	5.9	1.2
Q9	Your control of your personal information lies at the heart of your privacy.	6.2	1.
Q10	I believe that online privacy is invaded when control is lost or unwillingly reduced as a result of a marketing transaction.	5.7	1.3
Q11	Companies seeking information online should disclose the way the data are collected, processed, and used.	6.7	.6
Q12	A good consumer online privacy policy should have a clear and conspicuous disclosure.	6.8	.6
Q13	It is very important to me that I am aware and knowledgeable about how my personal information will be used.	6.6	.7

4.6 Limitations

Our study has few limitations. First, our study sample is biased towards young, female students, and might thus not apply to the general public. Second, we investigated users' perceptions towards wearable physiological sensing by means of one example, that is EMG, and by using use case videos. Future work should investigate if and how our recommendations apply to other physiological sensing technologies as they become more ubiquitous. Lastly, experimenter bias is a known limitation for qualitative experiments. As such, alternative names may be given to themes. However, we believe that this does not impact the resulting discussion and design recommendations.

5 Results

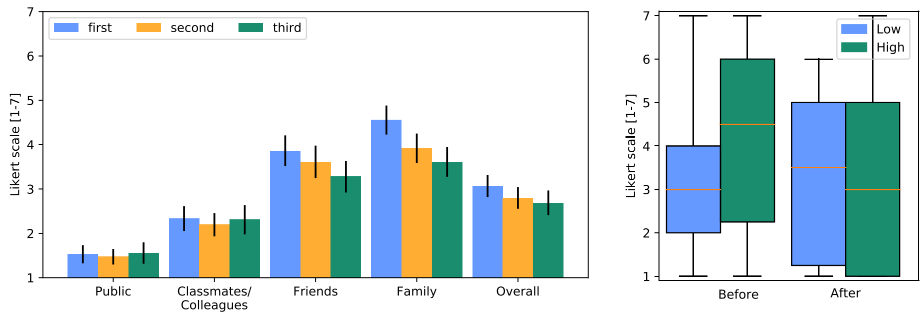
We conducted a between subjects study with 36 participants. In the following, we first report on the questionnaires and second on the interview analysis. All reported Likert items are on a 7-point scale (1=strongly disagree; 7=strongly agree).

5.1 Questionnaire Results

We used a 10-item version of the IUIPC [47]. Using Q4 to Q13 (see *Sharing Behaviour & Privacy Questionnaire*, Table 1) we calculate the following measurements as described by Malhotra et al. [47]. Participants rated their *Awareness* on average with 6.7 ($SD = .5$), *Control* with 5.9 ($SD = .9$), and *Collection* with 5.8 ($SD = 1.$). Thus, overall they were aware of possible concerns (H1).

Sharing Behaviour (H2) We conducted Friedman tests for each group over time to understand if the fact that participants needed to explore and understand the data would change their sharing behaviour. We analyzed how likely our participants are to share their EMG data with others over the course of the study (see Figure 5a). After each of the use cases we asked them the same question (cf. *Intermediate Questionnaire*): "I would share this EMG data with $<$*recipient*$>$", with $<$*recipient*$>$ being "public", "classmates/colleagues", "friends", or "family" [44]. Additionally, to see if there is an overall trend in our analysis, we conducted five Friedman tests. Our analysis showed a significant decrease in willingness to share EMG data with the family ($\chi^2(2) = 12.9$, $p < .002$) as well as an overall decrease ($\chi^2(2) = 6.4$, $p < .043$). We found no significant effect for public, classmates/colleagues, and friends ($\chi^2(2) = .743$, $p > .689$; $\chi^2(2) = 2.$, $p > .367$; $\chi^2(2) = 1.882$, $p > .390$; respectively).

Usage of EMG wearables (H3) To understand if Detail had an effect on the likelihood that participants want to use EMG wearables in the future, we conducted an analysis of covariance (ANCOVA) based on the initial and final question; see Figure 5b. Due to the unequal ratings before the study of the two groups, we analyzed the changes resulting from the variable Detail. Furthermore, as related work showed an impact of gender on privacy attitudes [20] and technology acceptance [69], we



(a) Share willingness

(b) Future EMG usage

Fig. 5. (a) Change in willingness to share EMG data with certain groups over the course of the study. (b) Change in likelihood that a participant wants to use EMG wearables in the future based on the experience in the study independent for DETAIL.

used gender as a covariate. We applied the Aligned Rank Transform (ART) [76] to the Likert items. Our analysis revealed no significant main effects for DETAIL ($F_{1,32}=1.506$, $p=.228$). We found that participants were very sensitive to their data and had privacy concerns already prior to the study, see Table 1.

5.2 Interview Results

We conducted interviews with 36 participants. We transcribed the interviews literally while not summarizing or transcribing phonetically. This technique is known to offer a subjective experience [6]. A total of three researchers were involved in the interview analysis. First, two researchers independently went through the printed transcripts of three participants and established an initial coding tree. As conflicts were resolved directly, we did not calculate inter-rater reliability. Then, one of them coded the rest of the data in a bottom-up manner and established the final coding tree (i.e., while iterating through the rest of the answers, new themes were defined). Finally, three researchers employed a simplified version of qualitative coding with affinity diagramming [31], which resulted in the themes we discuss below. While participants in our study had the option to express thoughts freely, they did not specifically comment on the use cases and visualization approaches. Rather, we found overarching themes regarding usage of EMG wearables, sharing behavior, personal data perception, and privacy challenges.

We conducted the interviews in our maternal language while only translating single quotes. We cite participants' IDs as well as study groups (*low* or *high* with regards to the variable DETAIL).

Usage of EMG Wearables The interviews revealed details on whether or not and how participants would make use of EMG wearables. Two participants (one of each group low, high) would use it if it is comfortable (in terms of wearing and ease of use). Most participants (12 of group low, 14 of group high) would use EMG only if the purpose would suit them. Specific purposes included sport, health, monitoring stress level, or sleep.

It must have a purpose and utility. A relief for everyday life. (P19, low)

[as an interaction], where it is simply helpful or it facilitates my work. (P3, low)

On the other hand, participants also named potential risks of usage. Here, four participants named radiation or malfunction of devices.

Sharing Behaviour Four participants (two of each group low, high) expressed being aware of the fact that wearable (EMG) devices would collect and potentially share personal data. These concerns are related to concerns of personal data (H1) and sharing habits (H2).

I know, if I buy such a device, I have to share some of my data and this is okay for me. (P29, low)

However, most participants expressed to prefer, on one hand, transparency (i.e., knowing that data is been shared) and on the other hand control (i.e., choosing actively to share or not to share their data). Depending on the purpose, participants were willing to share their EMG data.

If it [sharing the data] has a benefit for me, then I would forego my privacy. (P11, low)

Specific use cases, for which P11 would share data, include medical studies or personal benefits. 6 participants rated sharing as less critical in case of anonymized EMG data.

Participants described how they would react in case EMG data would be revealed unintendedly. Some participants would actively fight unauthorized data reveallation (i.e., 8 participants would take legal action). Others were more passive (i.e., would not explicitly take action) while still disliking personal EMG data being revealed.

Personal Data Perception During the interviews, we discussed how personal participants would perceive their EMG data: less, more, or as privacy sensitive as "other" personal data (e.g., name, birthday).

If I think about what is possible with this [EMG] data through processing, I think it is important to me to protect this data in the same way as my other personal data. (P24, low)

This awareness further underlines that users are in fact concerned with sharing their data (H1). Further, participants strongly highlighted the difference between data they were or were not identifiable from (H2).

You cannot even say who I really am. (P27, low)

Privacy Challenges & Threats 12 participants were concerned about being tracked and surveyed by the service provider or even the government. 7 participants were worried about being refused for health insurance, in case the insurance would know their EMG data. Privacy plays an important role, but also depends on the context for many participants. Health data was named as particularly concerning

(5 participants). Some already mentioned possible attacks (i.e., data leaks) and were concerned about misuse of their data. New threat models may evolve around physiological data and users' health.

5.3 Summary

Most participants expressed concerns about sharing their private physiological data. However, only few of them would take any action against undesired sharing. At the same time, anonymous sharing or sharing for a certain purpose would be more acceptable for participants. Hence, we confirm that users are *concerned about their EMG data's privacy* (**H1**). We showed that participants, who were more willing to share personal data prior to the study, were also *more willing to share their EMG data*, which confirms (**H2**). We revealed that working with the dashboard and *getting engaged with EMG data influences the willingness to share data*, thus confirming (**H3**).

6 Discussion

Based on our qualitative and quantitative results, we discuss how participants perceived collecting and sharing EMG data. Moreover, we discuss the insights on a more general level with respect to potential risks as well as opportunities for novel, intelligent and mobile interfaces based on physiological sensor data.

6.1 User Perceptions of Intelligent Wearables

Participants raised privacy concerns with regards to their personal data already prior to the study. However, they were willing to share their (potential) EMG data with close family and friends, who generally are known to be more trustworthy [9], yet they would only share for certain purposes (e.g., personal benefits or research). Additionally, participants highlighted potential risks connected to physiological sensor data, e.g., if health insurances would get hold of users' physiological data. This leads us to assume that users are generally not reluctant to employ novel, intelligent wearables if they would only fit their need and purpose, which is in line with the privacy calculus theory (i.e., users outweigh their personal benefits over perceived risks, cf. e.g., [46]). However, we can also confirm **H1**: users are concerned about sharing personal EMG data.

6.2 Unaware Users

Participants of our study stated that collecting EMG data anonymously would not be critical to them (e.g., referring to P27: *"You can not even say who I really am."*). Thus, they are aware of data type, however, not all are concerned with sharing the data (**H1**) and may not change their behaviour (**H2**). However, preserving anonymity needs special attention as it has been shown that datasets can be de-anonymized [60]. Thus, while physiological sensor data has a great potential to inform user interfaces and users are even fine with the data collection, we argue that users may not be aware of the potential risk and danger their own data bury. Hence, we argue that data should not be hidden from the user, and the user should always be in control of their data being shared and especially the data that is not shared with the public and thus mostly hidden to the user. This may ultimately address users' concerns (**H1**) and change their sharing habits (**H2**).

6.3 Enabling an Improved Health Awareness

We found that our participants are open to try EMG-based wearables, especially for use cases that fit their daily needs and habits. They are open to interaction concepts which use EMG as a signal to trigger interactions, like the Myo wristband. More importantly, they are also open to use EMG to foster a better awareness about their own physiological state, for instance, on a dashboard or app. This brings great potential for new quantified self platforms, but also carries responsibility to convey the right data.

In our case, we employed mock visualizations and use case videos showing EMG data in our study. We carefully designed our visualizations to match current dashboards based on physiological data, and our use case videos as neutral as possible. While these may limit our results to connotations we may have communicated unintendedly, we see great potential in future visualizations informed by EMG, supporting various health related use cases, such as informing users about their current state and potentially giving recommendations or advise for health and well-being. This can especially be adopted by people within the "quantified self" movement. Having in mind that users are concerned about their data, it is important to provide them with the necessary information for making informed decisions. This can be achieved by providing users an appropriate level of detail in the data visualization, which may positively impact their opinion on recording and sharing sensor data (**H3**).

7 Design Implications

From the insights and results gained through our study, we derived a set of implications for the design of future EMG-based interfaces, which also align well with general physiological sensor-based interfaces. In particular, the relationship between user and provider as well as users' behavior of sharing data with others is not specific to EMG. As participants were generally concerned about (mis)use of their data and wished for transparency and control, we suggest to *educate users*, let them *stay in control*, and *inform* them about data policies. Moreover, as participants were generally more willing to *share data with trusted individuals* and/or for certain purposes with *third parties*, we discuss respective implications.

7.1 Educating Users

As participants asked for transparency, we suggest to *not hide data*. In line with related work (e.g., [56]), users wish to be aware of their data being collected. Means to address this include, but are not limited to, providing users means for reviewing all tracked data in detail, e.g., through clear and understandable data visualizations and videos like we did during our study. Other options are to provide indicators at devices when data collection is active (similar to, e.g., webcams) or visualizing spaces of data tracking by means of augmented reality (AR) [56]. Besides showing and describing the collected data, it is important to inform users about potential risks and assess their comprehension. This could be done through questions asked upon the setup of a device that is capable of collecting physiological data. Another possibility is to let users solve tasks similar to the ones used in our study but using their collected data and providing them visualizations. This would not only support understanding, but also internalizing the collected data, which is equally important.

7.2 Let Users Stay In Control

We propose to *let users stay in control* of what happens to (which parts of) their data. In particular, users should be able to decide which sensors are actively *tracking*. In addition, users should also stay in control in cases of combining data.

As an example, *combining* physiological data with location data (e.g., obtained from the wearer's smartphone) may create additional insights but at the same time make information even more sensitive. Control is also important in the context of *data storage*. Users should have the possibility to select whether the generated data is stored over longer time periods (e.g., to observe their own behaviour) or if they only allow for real-time assessment of the data (e.g., current stress level). Furthermore, users should be able to choose the level of *aggregation* for their data. Though not apparent from our results, users of future physiological sensing wearables may want to look at the raw data instead of aggregated data visualizations and use it for fine-grained data analysis later themselves. This would also allow for personal interpretation of own data.

7.3 Inform Users about Data Storage Aspects

As participants expressed concerns regarding storage and processing of data, we suggest to inform users about all aspects related to *data storage*. This includes where it is stored, to whom it is transferred, and by whom it is processed (in particular for entities beyond the provider of a devices or service). In compliance with data protection laws and regulations such as the General Data Protection Regulation (GDPR), it should also be possible to ask for all data to be deleted at any time, in case the user wishes to do so.

7.4 Sharing with Trusted Individuals vs. Third Parties

Our results show that participants are more willing to *share their data with trusted individuals* than with a general public. Hence, users should have the option to select sharing EMG data with their partner, family, and/or friends. Users should also be able to decide what parts of the data are exactly being shared. Additionally, users should have the option to hide different levels of detail or to share a modified version of the data. The EMG wearable device should allow raw fine-grained data to be accessed first to then decide which level of *aggregation* or which combination of data to share. As an example, for tracked steps it might be that users want to share their achievement, but without the corresponding location data.

Participants also mentioned that they would be willing to *share their data with third parties* for certain purposes. As an example, participants mentioned support of studies (that they may benefit from in the long term). Furthermore, while users might be fine with their service provider having access to their personal data, for third parties they might want data to be anonymized prior to sharing.

A risk index could facilitate users' sharing decisions. Such an index would inform users about risks associated with sharing particular data. As an example, higher gait activity in the EMG data might hint at users currently not being at home.

8 Conclusion

In this paper, we investigated users' view on wearable electromyography (EMG). We conducted a user study with 36 participants to evaluate users' perception towards privacy of physiological data obtained from wearable EMG. We found that participants were indeed generally concerned about the privacy of this data. Furthermore, we found that when participants analyzed EMG data, it became less likely that they were willing to share this data with others. Based on our findings, we derive a set of guidelines for designers of future applications based on EMG or other physiological data. Our guidelines are meant to support protecting users' privacy, better inform them about involved risks, and ultimately support the uptake of this technology. We suggest to not hide data from users and enable them to explore the data to asses possible risks. Moreover, we found that it is important to give control to the user on which data to share and with whom.

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