On Stress: Combining Human Factors and Biosignals to Inform the Placement and Design of a Skin-like Stress Sensor

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ABSTRACT

With advances in electronic-skin and wearable technologies, it is possible to continuously measure stress markers from the skin and sweat to monitor and improve wellbeing and health. Understandably, the sensor's engineering and resolution are important towards its function. However, we find that people looking for an e-skin stress sensor may look beyond measurement precision, demanding a private and stealth design to reduce, for example, social stigmatization. We introduce the idea of a stress sensing "wear index," created from the combination of human-centered design (*n*=24), physiological (*n*=10), and biochemical (*n*=16) data. This wear index can inform the design of stress wearables to fit specific applications, e.g., human factors may be relevant for a wellbeing application, versus a relapse prevention application that may require more sensing precision. Our wear index idea can be further generalized as a method to close gaps between design and engineering practices.

CCS CONCEPTS

• **Human-centered computing** → **User studies**; • **Hardware** → *Flexible and printable circuits*; • **Applied computing** → Health informatics.

*Both authors contributed equally to this research.

KEYWORDS

wearable electronics, electronic-skin, bioelectronics, mental health, mental wellness, precision psychiatry, heart rate variability, skin conductance, cortisol

1 INTRODUCTION

Daily stress is defined as the body and mind reaction to routine stressors, i.e. challenges of day-to-day living. These stressors can either be predictable (*e.g.,* daily commutes) or unpredictable (e.g. a sudden deadline) and occur in 40% of all days [1]. Daily stress has been shown to cause psychological distress and exacerbate symptoms of existing physical health conditions [41]. Repeated triggering of daily stress can also lead to chronic stress, which has been associated with a variety of pathophysiological risks—conditions that impair quality of life, shorten life expectancy, and lead to developing mental illness [17, 41]. Despite its prevalence, we have no objective tests or scalable technologies for detecting stress on time to help design stress management interventions.

One promising area of research focuses on the continuous sensing of physiological and biochemical data using wearable sensors (ẅearables)̈, widely used for lifestyle and medical monitoring [13, 34, 44]. When designing these wearables, biosignal acquisition often dictates design choices, such as form factor, while user needs are a secondary concern. However, in the case of wearables for wellness and health applications, such as stress management, both biosignals and human factors are important to consider to improve adoption and adherence, especially when used for preventative purposes. Common form factors include wristwatches and emerging adhesive bandages (*e.g.,* SenseON and AMPStrip [56]). Watch-based sensors are the most common, but they tend to provide less data granularity and are difficult to integrate for precision applications. Additionally, users may often take them off, making it difficult to obtain continuous data [24]. As a result, there has been increasing interest in electronic-skin (e-skin) wearables that are not only able to extract new metrics, such as cortisol (a hormone directly related to stress), but also more private, more flexible in form factor, disposable, easy to apply across the body, and potentially more comfortable compared to hard electronics (Fig. 1). These advantages can help boost new designs of personalized solutions for stress management.

In this work, we examine how healthy users might react to an e-skin wearable device prototype designed to help them manage stress. Based on a collaborative effort between human-computer interaction (HCI), chemical engineering, and psychiatry researchers, we present a way to combine human factors with biosignal data to inform future designs. Our research questions include: *Where would healthy users be comfortable placing an e-skin stress sensor on their bodies and why? How might their preferred placement locations impact signal strength for electrophysiology (HRV, EDA) and biochemical (cortisol) stress markers? And, can we unify these two visions in a single design parameter?*

To answer these questions, we collected three sources of data: human factors, on-skin electrical and optical biosignals, and sweat biochemical biosignals. First, we investigated n=24 healthy users on their perceptions and preferences for e-skin wearables for stress management, factors that contribute to adoption and adherence, and explored how these preferences might change after a short wear session. We complemented these data with on-body biosignal data, namely heart rate variability (HRV) and skin conductance (SC) (n=10), and sweat-based cortisol levels (n=16) sampled at some of these preferred/not preferred body locations.

Our results suggest that, while the wrist and the forehead are rich for sensing, users tend to prefer more discreet wear locations for privacy, such as the upper arm and torso. Thus, we used a combined weighting mechanism to merge both human factors and biosignals (Fig. 1c). This weighting yielded the upper arm as one of the most desired wear locations, followed by the forearm. Our results also suggest that stigmatization of stress management is a key design factor and that factors such as comfort, size, and concealability were viewed as critical to adoption and factored into participant's choice in where to wear our stress management prototype.

In summary, the contributions of this work include (i) a multidisciplinary effort for combined user-centric and biosignal data acquisition, (ii) a visualization and weighting approach that balances user-centered design with engineering-centered biosignal measurement into a single "wear index" to identify wear locations for designing stress wearables, and (iii) a discussion on the potential use cases for this methodology and to extend it beyond stress management to close the gap between design and engineering approaches to build wellbeing and health wearable sensors.

2 RELATED WORK

2.1 Adoption of E-skin Wearables

2.1.1 Medical Applications. Existing medical wearables range from diabetes monitoring devices to adhesive patches for contraception (*e.g.,* [49]) or smoke cessation (*e.g.,* [15]). E-skin, devices are a relatively new and experimental class of medical wearables. E-skin wearables tend to be devices made of flexible plastics [35, 55], or more experimental substrates (*e.g.,* organic polymers), containing electronic or biochemical components [50, 72]. The construction of these devices is complex and often blends material sciences, biochemistry, and numerous other disciplines to create technologies capable of seamlessly monitoring wearers to provide a wealth of data for care providers. However, many existing medical wearables in commercial and academic domains focus on biosignal quality because they are often designed for short-term monitoring with the goal of acquiring high-quality medical data. For example, electrocardiography (ECG) data is the most important factor for a heart monitoring patch, and it is typically worn for about 14 days for diagnostic purposes.

While biosignal quality is very important, it is necessary to examine human factors during the design process, particularly when considering long-term continuous monitoring. For example, privacy concerns with respect to how biosignal data might be accessed or who might have access could be a concern for some users considering engaging in monitoring actionable medical information. Moreover, Garabet et al. [20] found that the degree of acceptability of the design was related to the perceived control the wearer had may greatly impact the perceptions of passive e-skins.

2.1.2 User-centric Exploration. Human-Computer Interaction (HCI) and Ubiquitous Computing studies have been exploring the use of

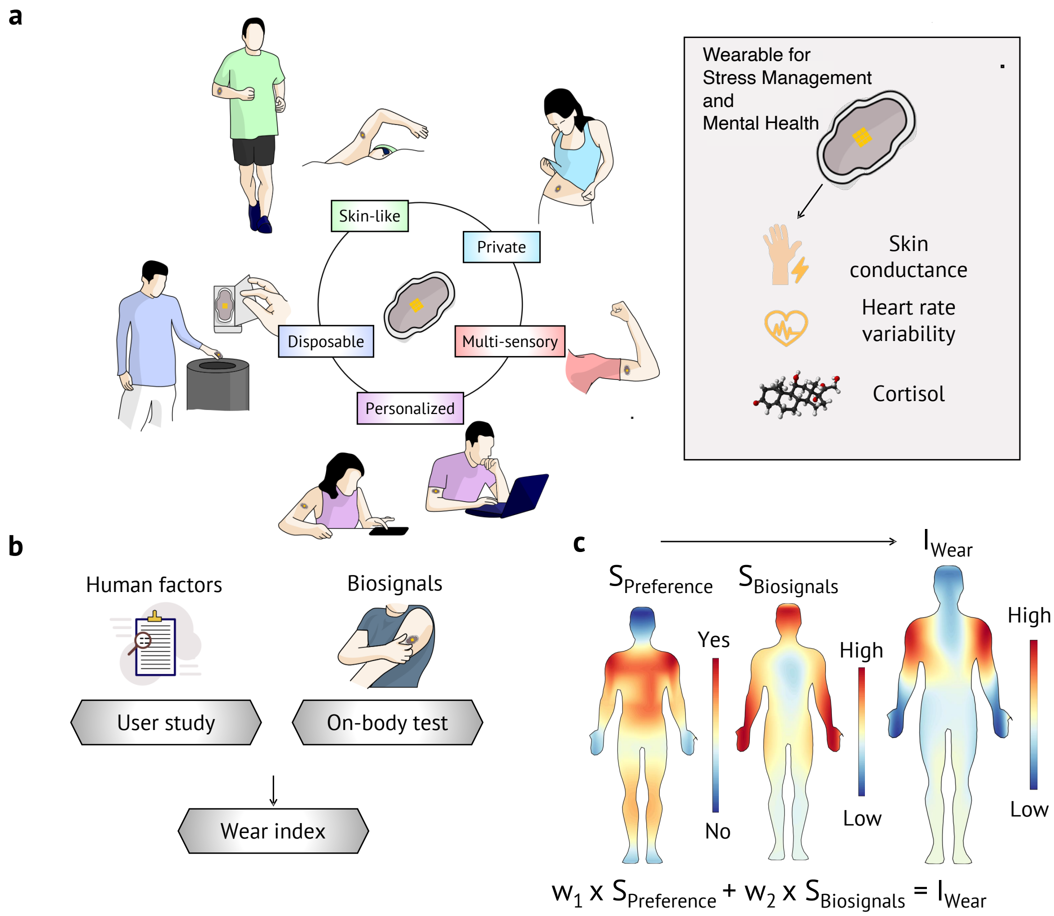


Figure 1: Skin-like stress sensor design process. (a) Desired engineering design properties of the device: (i) *skin-like* and imperceptible; (ii) *private* - safeguarding sensitive data; (iii) *multi-sensory* - collecting necessary physiological biosignals such as skin conductance (SC), heart rate variability (HRV), and cortisol levels; (iv) *personalized* - tailored to each individual, and use case; and (v) low-cost and *disposable* to ensure ease-of-use and reliability. (b) Overview of the combined design approach used in this study. We collected user preference data from a user study, and performed on-body sensing to assess the quality of the biosignals at the preferred body locations. Then we weighted both human factors and biosignal qualities to create a combined wear index (I_{wear}) for different body locations. (c) Visual depiction of wear location combining user preference data ($S_{Preference}$) and biosignal data ($S_{Biosignals}$) used to find desired wear locations (I_{wear}).

wearable technologies for more than a decade ([5, 19]), as well as studies of digital phenotyping using smartphones and wearables for mental health monitoring[14, 51]. The majority of e-Skin applications have focused on exploring new materials (*e.g.,* [26]) or fabrication methods (*e.g.,* [40]) that support touch interactions with personal computing devices [38, 67, 68]. In addition, researchers have explored user reactions to such devices [27, 37] and differences across cultures (*e.g.,* [25]). With regard to their use in public, findings point to two extremes, from users who are interested in adopting the technology to those who are more averse to their use even by others [28, 48, 70]. As a result, there is an increasing interest in studying early user reactions to make recommendations about design, form factors, and properties to increase the likelihood of adoption.

2.2 Biosignal Measurement

A growing body of literature indicates physiological parameters such as HRV [2, 11, 31], SC [10, 53, 62], and biochemical signals such as cortisol [9, 36, 43, 58] are linked to stress, anxiety, and depression [12]. SC measures the eccrine sweat gland activity in response to stress [10]. HRV measures the balance between the autonomic nervous systems—sympathetic (SNS) and parasympathetic (PNS). SNS gets activated when facing threats or stressors, while PNS handles the body's relaxed state [8]. Finally, cortisol is the body's main stress hormone. In response to internal or external stressors, cortisol is released from the adrenal glands and puts the body into a heightened alert state. Chronic activation of the stress-response system results in overexposure to cortisol, which can disrupt almost all body processes [57]. Thus, monitoring biosignals is increasingly viewed as fundamental in diagnostics and precision health [18].

One challenge for these wearable sensors is signal acquisition and maintaining quality in the field. HRV and SC are normally collected with desktop signal acquisition units, while cortisol levels in bodily fluids are measured using enzyme-linked immunosorbent assay (ELISA) [22] and liquid chromatography/mass spectrometry (LC/MS) in lab settings. Signal strengths of SC, HRV, and cortisol also vary significantly on the body. HRV is often derived from the photoplethysmography (PPG) signal, which depends on the arterial blood signal collected by an optical sensor. The higher the signal from the arteries, the better the PPG signal quality. Therefore, locations where the arteries are near the skin's surface provide excellent PPG signal. The forehead and the underside of the wrist are usually good choices for reflection-mode PPG sensing [32, 33]. On the other hand, SC depends on the density of the eccrine sweat glands, which is highest on the fingers and the shoulders, but drops roughly by half on the wrist and the arm [6, 59, 64] (Fig. 1c). van Dooren has shown opportunities to extend traditional SC sensing from the hands to feet and shoulders in ambulatory settings [64], which shows an opportunity to try biosignal acquisition in other parts of the body. Again, this work was done in isolation only for SC data, without other biosignals, and without considering human factors.

As for cortisol sensing, saliva or sweat is typically collected and sent to the lab to be analyzed. Gathering a large enough sample for analysis is often an invasive process. Samples must be properly stored for transport, tend to degrade over time (e.g, due to evaporation), and the technology used to analyze samples is prohibitively expensive [7]. However, recent advancements in e-skin and wearable technology are making it increasingly easy to measure these signals (*e.g.,* HRV [42, 63], SC [47, 69], and cortisol [46, 61]) at the sources where signals are strongest.

2.3 Wearable Sensor Placement

There have been few studies that aim at understanding the placement of wearable sensors based on more than just technical or design issues. For example, Zeagler developed various body contour maps that incorporate social and technical aspects such as motion impedance as a concern or that certain areas of the body are optimal for PPG sensing [71]. However, these factors were viewed retrospectively, and we are unable to know if they were dominated by engineering or social parameters. Although Zeagler's contours informed some elements of our data-collection process, we decided to directly study where people prefer to place stress sensors, because the impact of social stigmatization was not captured in Zeagler's work. In this work, we use a multi-factorial (human factors and biosignals) design approach (Fig. 1c). We combine wearability preferences ($S_{Preference}$) with biosignal intensities ($S_{Biosignals}$). We then proposed a combined wear index created using a weighting mechanism: ($I_{Wear} = w_1 \times S_{Preference} + w2 \times S_{Biosignals}$). We then visualize this data to explore tradeoffs between how $S_{Preference}$ and $S_{Biosignals}$ are utilized to suggest optimal wear locations.

3 MULTI-FACTORIAL DATA COLLECTION AND INTEGRATION

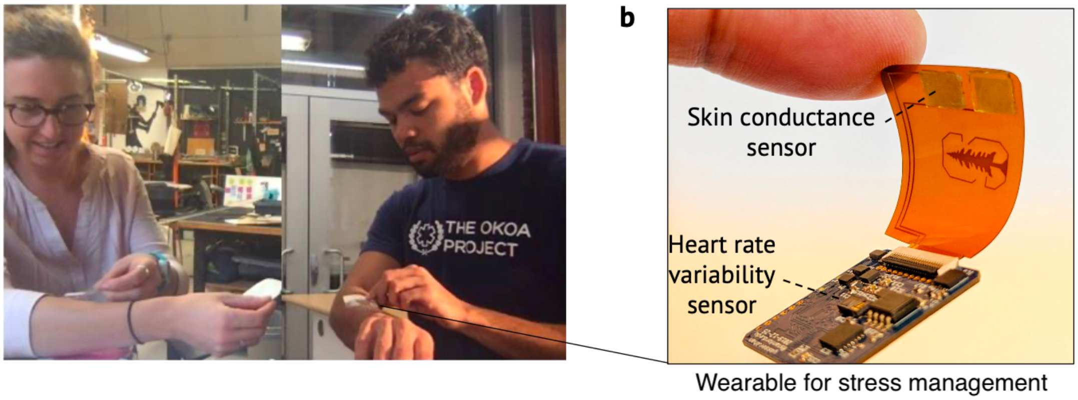
We present three methods to collect Human Factors, On-Skin Physiology, and Biochemical data. Three teams of researchers from HCI, Chemical Engineering, and Psychiatry collected each dataset, respectively, following best practices for human factors, biosignal engineering design, and psychophysiology data collection procedures, with their respective limitations and caveats. All data collection procedures followed IRB protocols approved by the Committee for Protection of Human Subjects at our university (protocol no., IRB-45825 and IRB-41837). The data collected was then integrated into a single combined index and visualization to balance human factors and biosignals.

3.1 Custom-built Sensor

Both human factors and biosignal data, except for cortisol, were obtained using a custom-built wearable sensor depicted on Figure 2b. This sensor had two modules, a flexible electronics (e-skin) module to be used for microfluidics sweat extraction (1 inch x 1 inch), and a hard electronics module (1 inch x 1 inch) used for increased accuracy of the Skin Conductance (SC) and Heart Rate Variability (HRV) on-skin data (2 inch x 1 inch overall). To obtain valid human factors data, the HCI team kept both modules, despite the possibility to have simulated a fully flexible version. The sensor included a pair of electrodes with hydrogel for SC data, and an optical sensor for HRV interfaced with the nRF52832 Bluetooth transceiver using a serial peripheral interface (SPI). We ensured a typical range of 0-50 μS for SC using a feedback loop with a Texas Instruments TLV9102, dual 1MHz, 16-V rail-to-rail op amps to guarantee <10μA current flows. The output signal was sampled using a 12-bit analog-to-digital-converter (ADC) of a Nordic Semiconductor nRF52832 Bluetooth transceiver. The HRV signal was obtained from PPG signals collected by an optical sensor SFH 7050 from OSRAM Opto Semiconductors Inc. Red (660 nm) and NIR (950 nm) lights were used to collect the PPG signals at 100 Hz sampling frequency. The NIR signal was used in a peak detection algorithm to find the systolic peaks. HRV was calculated using a time-domain RMSSD metric $\sqrt{\frac{\sum_{i=1}^{n-1}(Peak_i - Peak_{i+1})^2}{n-1}}$ from a window of n=5 systolic peaks.

3.2 Data Collection 1: Human Factors

3.2.1 Procedure. To assess user perceptions of this emerging e-skin sensor for stress monitoring the HCI research team applied a two-part design probe method. First, we set up three public kiosks at a university café, university bookstore, and local public library. We recruited passersby for brief semi-structured interviews (*Median*=24 min, *SD*=4.5 min). In addition to questions about wearable device use, participants marked on paper body contour maps (*Supplementary Fig. 3*) where they would and would not wear an e-skin stress sensor while "thinking aloud" to explain their rationale. Participants then attached a non-working low-fidelity version of our custom-built e-skin sensor (Fig. 2a and *Supplementary Fig. 4*) to their preferred body location using medical grade tape. The lo-fi prototype had a similar form factor to the wearable used to collect biosignals (Fig. 2b) in terms of size, shape, and weight, as well as the planned attachment method. After a short experience, participants a b



c

Body location	Yes	%	No	%
Upper torso	17	71%	2	8%
Upper arms	16	67%	2	8%
Middle torso	11	46%	6	25%
Thighs	11	46%	9	38%
Lower torso	9	38%	4	17%
Pelvis	9	38%	12	50%
Legs	7	29%	3	13%
Ankles	6	25%	3	13%
Forearms	6	25%	5	21%
Armpits	6	25%	6	25%
Knees	4	17%	8	33%
Neck	3	13%	9	38%
Wrists & hands	2	8%	12	50%
Feet	1	4%	11	46%
Face/head	1	4%	19	79%
Elbows	0	0%	4	17%

d

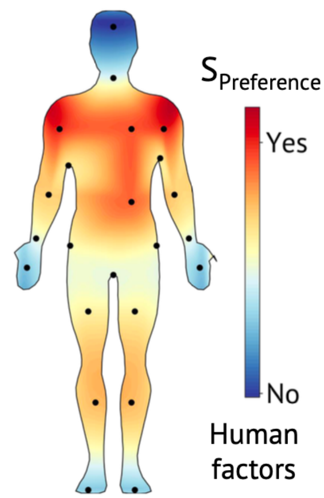


Figure 2: Summary of human factors data collection procedure. (a) Participants interacting with lo-fi devices with the same form factor of the custom-built wearable. (b) Custom-built sensor utilized for collecting SC data (using hydrogel-coated electrodes) and HRV data (derived from photoplethysmography (PPG) signals obtained by an optoelectronic sensor). (c) Summary of body locations where they would prefer to wear (Yes/red) or not to wear (No/blue) the device - the complete dataset is provided in *Supplementary Fig. 5*. (d) Summary body contour plot showing positive preference (red), and negative preference (blue), and dots indicating the places (from table c) that participants marked on paper body contours.

completed a short survey (derived from the WEAR scale [29, 30]) about demographics, comfort, and perceived social acceptability. Participants were then asked if they would like to change the location of the probe (*e.g.,* to a potentially more comfortable location) and, if not, to go about the rest of their day while continuing to wear the prototype, to later complete a post-study survey about their experience. If they changed the location of the prototype, participants were asked to explain why they did it. The follow-up survey was emailed to participants on the evening of their participation. Participants received 3/4 of their compensation after completing the first part and the remainder for completing the follow-up survey at the end of the day. A depiction of the complete procedure can be found in *Supplementary Fig. 1*.

We recruited n=24 participants (12 male, 11 female, 1 non-binary) whose age was (*Mean*=35.8, *Median*=28, *SD*= 15.4). Most (79%) had bachelor's and higher education, and most (79%) were white or asian, working full-time (50%) or studying (38%). Perceived Stress Scale (PSS-4) [23, 66] indicated that most experienced moderate levels of stress over the last month (*Median*=6.44, *SD*=3.29) as shown in *Supplementary Fig. 2*.

3.2.2 Data Pre-Processing. Data from this study includes survey responses, paper body contour maps, and interview transcripts. Descriptive statistics were calculated from closed-form survey results and body contour maps, while open-response questions were thematically analyzed. All interviews were professionally transcribed for computer-assisted qualitative data analysis. A researcher designed a preliminary codebook based on our research questions and concepts raised in prior literature. Two other researchers independently coded random selections of 12% of the interview transcripts according to the preliminary codebook, and inter-rater reliability (IRR) was measured using Cohen's kappa (κ). Between rounds, the researchers met to resolve disagreements and update the codebook. An overall κ=0.83, considered an almost perfect agreement, was achieved after two rounds of coding. The remaining interviews were then independently coded by the two researchers.

3.2.3 Preferred On-Body Placement. Participants showed a strong preference for the upper arms and upper torso (*i.e.*, chest and back) followed by the stomach, waist, and thighs (Fig. 2c). Participants reported that concealability and comfort were the top decision factors. Thus, we note that all these body locations are usually covered by everyday clothes (*e.g.,* t-shirt, shorts). On the other hand, visible locations such as the head and extremities (*i.e.*, hands, wrists, and feet) were undesirable. Similarly, they disliked locations where the placement of the wearable would interfere with the body's natural movement (*e.g.,* elbows, knees). A condensed version of the body map results is shown in Fig. 2d, where red indicates desirable locations, blue indicates undesirable locations, and points represent the locations listed in Fig. 2c. The complete set of results is presented in *Supplementary Fig. 5.*

3.2.4 Additional Qualitative Findings.

Prior Experience with Wearables. A majority of participants (87%, 21/24) associated wearables with wrist-worn technology for fitness tracking, in particular, smartwatches. A third (33%, 8/24) defined wearables as devices that monitor user's health. Nearly half mentioned medical devices as examples of wearables including heart monitors, nicotine patches, and hearing aids. While some (17%, 4/24) had worn wearables for fitness or medical reasons, only a small fraction (8%, 2/24) used a wearable at the time of the interview. A majority (75%, 18/24) did not see a utility in a wearable that was not covered by other devices like their smartphones. High cost and lack of comfort were also reported as barriers to ownership. Of the few using a wearable, most cited utility and comfort as top criteria in selecting devices.

Adoption and Social Acceptability. Most participants (58%, 14/24) expressed interest in e-skin wearables for stress monitoring. A majority (79%, 19/24) said they would be more likely to use it if their doctor recommended it. Of those not interested, over a third (37%, 5/14) said medical advice would not impact their decision. More than half (58%, 14/24) said appearance is an important factor, emphasizing that the ideal wearable should be fashionable ([16]) and inconspicuous - seamlessly blending in with the wearer's attire to avoid unwanted attention. A third (33%, 8/24) said a wearable would be more acceptable if it was part of a social trend normalizing stress management. While participants were initially somewhat concerned about judgment by others, after wearing the device, their interest in the e-skin wearable increased, and showed less concern that the wearable might make others uncomfortable, cause awkwardness, or result in them being ridiculed. However, paradoxically, they became more worried about what the device might communicate about them—being marked as someone in need of stress or mental health support (*Supplementary Fig. 6*).

Usability. Assuming an ideal scenario where a wearable is cheap, durable, and waterproof, most participants would prefer to change it *weekly* or *bi-weekly*, with some of them choosing *daily* or *monthly*. Participants rationalized these choices by balancing personal hygiene, signal continuity, convenience, and cost (*Supplementary Fig. 7*).

3.3 Data Collection 2: On-Skin Physiological Biosignals

3.3.1 Procedure and Participants. Volunteers were asked to put on the sensor attached with medical tape for 2 minutes to obtain SC and HRV data on 6 different locations (1. wrist, 2. forearm, 3. upper arm, 4. forehead, 5. upper chest, 6. stomach), while remaining in a calm seated position (Fig. 3a). Although the wrist and the forehead were not preferred locations indicated in the human factor study, we chose the forehead due to the high biosignal intensities and the wrist because most commercial wearables are wrist-worn. n=10 volunteers (6 male, 4 female) were recruited from among healthy university graduate student population (age mean = 26).

3.3.2 On-Body Biosignal Magnitudes. Fig. 3b shows the average PPG signal magnitude and variation at different places on the body. NIR PPG signal was normalized for each participant, and the average value (bar height) and the standard deviation (error bar) of the normalized data are shown in Fig. 3b. The complete dataset of n=10 participants is shown in *Supplementary Fig. 8.* The forehead provides the highest signal magnitude (100%). For NIR light, the average normalized PPG signal percentages are approximately 49, 17, 13, 100, 2, and 4 on the wrist, forearm, upper arm, forehead, upper chest, and stomach, respectively. The reproducibility of the measurement is shown in *Supplementary Fig. 9*, where 5 consecutive PPG measurements were collected from one participant while donning and doffing the sensor for each measurement. The upper chest showed the lowest signal magnitude and was susceptible to motion artifacts during breathing. A similar study was performed for measuring SC.

We observed SC with average normalized percentages of approximately 29, 39, 32, 100, 27, and 24 on the wrist, forearm, upper arm, forehead, upper chest, and stomach, respectively. The SC data was normalized for each participant, and the average value (bar height) and the standard deviation (error bar) of the normalized data are shown in Fig. 3c. The complete dataset of n=10 participants is shown in *Supplementary Fig. 10.* We performed a reproducibility study of the SC sensor, which is presented in *Supplementary Fig. 11.*

Figure 3d(1) shows the wrist data of a single volunteer. Figures 3d(2)-(6) show the red and NIR PPG signals and SC from the forearm, upper arm, forehead, upper chest, and stomach, respectively. The PPG signal is pristine on the wrist and the forehead, but gets attenuated on the forearm and the upper arm. To calculate HRV, it is imperative that the PPG signal quality is good enough for proper peak detection. Figures 3d(1)-(4) show that the NIR PPG signals on the wrist, forearm, upper arm, and forehead are adequate for peak detection. However, on the upper chest and the stomach,

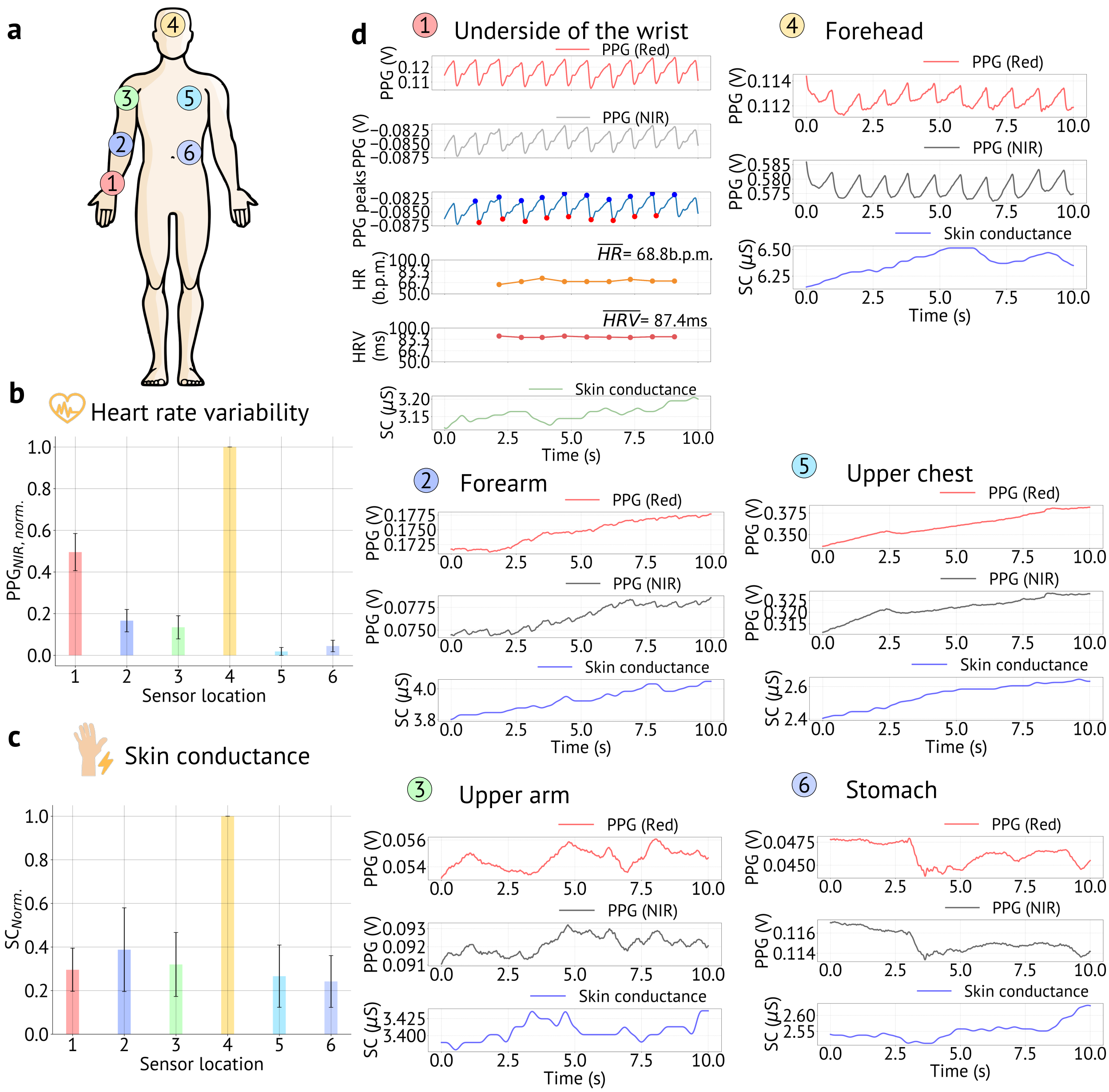


Figure 3: Heart rate variability (HRV) and skin conductance (SC) data distribution on the body. (a) Sensor placement locations - (1) wrist, (2) forearm, (3) upper arm, (4) forehead, (5) upper chest, and (6) stomach for *n*=10 participants. (b) Photoplethysmogharpy (PPG) signal magnitudes for near-infrared (NIR) light on the aforementioned 6 locations. HRV is derived from PPG, hence, PPG signal magnitudes are used in the analysis. NIR PPG signal was normalized for each participant (bar height = average, error bars = SD) (see *Supplementary Fig. 8* for a complete PPG dataset). The forehead shows the highest signal magnitude and gradually drops on the wrist, the forearm, and the upper arm. The signal is the lowest on the chest. (c) Variation of SC data normalized for each participant (bar height = average, error bars = SD) (see *Supplementary Fig. 10* for a complete SC dataset). (d) PPG from red and NIR channels, systolic and diastolic peaks from PPG, heart rate (HR), HRV calculated from PPG signal, and SC from the 6 locations. PPG signal is clear on the wrist, forearm, upper arm, and forehead, and gets attenuated on the upper chest and stomach.

the signals barely show PPG peaks, making the data unusable. Both on the chest and the stomach, the PPG signals become modulated with respiration - data where respiration affects the PPG signal is shown in *Supplementary Fig. 12*.

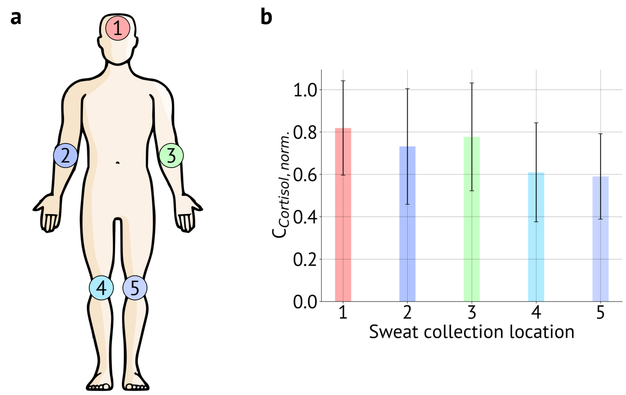


Figure 4: Sweat cortisol distribution on the body. (a) Sweat collection locations - (1) forehead, (2) right arm (cubital fossa), (3) left arm (cubital fossa), (4) back of the right knee (popliteal fossa), and (5) back of the left knee (popliteal fossa). (b) Sweat cortisol concentrations on the aforementioned 5 locations. Sweat cortisol concentrations were normalized for each participant in the *n*=16 participant study, and bar heights represent the average of the normalized value and the error bars represent the standard deviation of the normalized value. The complete dataset of *n*=16 participants is shown in *Supplementary Figure 13.*

3.4 Data Collection 3: Cortisol from Sweat

3.4.1 Procedure. Cortisol, a molecule highly correlated with stress, and present in body fluids, was collected separately from the e-skin sensor, which did not have the microfluidics capacity to extract enough quantities of sweat, nor the ability to elicit sweat directly using methods such as iontophoresis, which involves sending an electrical current to the epidermis to elicit sweat production. The psychophysiology team had the challenge to generate sufficient sweat to obtain a valid cortisol signal. This is a hard task, as normally cortisol is obtained from saliva, where cortisol concentrations are about an order of magnitude higher than sweat. The team decided to use a body temperature manipulation method that guarantees minimum quantities of sweat which was approved as part of a larger protocol. However, cortisol signal can be obtained from iontophoretically generated sweat as demonstrated by Wang et al. [65] and Torrente-Rodríguez et al. [61]. Furthermore, our latest generation of wearable has the capability of wearable cortisol sensing in addition to the SC and HRV measurements. *n*=16 volunteers were recruited to sit in a portable dry infrared sauna that zipped up around the chin. Their whole body was enclosed in the sauna except their head. The sauna temperature was set to 60 °C (140 °F). Volunteers remained in the sauna until either 45 min had elapsed, or until their core body temperature reached the maximum safety limit of 39.4 °C (103 °F). Volunteers had their core body temperature measured using an infrared tympanic membrane thermometer every 3 min that they were in the sauna to ensure that their core body temperature did not get too high. We collected sweat samples from participants as their bodies attempted to regulate their core body temperature. Sweat was collected utilizing an array of non-woven dental sponges to absorb the sweat from the skin surface. Dental sponges were affixed to the body using a transparent stretchable and waterproof medical dressing (Tegaderm, 3M).

3.4.2 Data Collection and Analysis. Data was measured in five body locations where there was a higher expectation of obtaining sufficient sweat from the manipulation. Sufficient sweat for appropriate cortisol analysis was collected from (1) forehead proximal to the frontal bone, (2) left and (3) right cubital fossa (inside of elbow), and (4) left and (5) right popliteal fossa (back of the knee). Once volunteers exited the sauna the sweat saturated dental sponges were placed in centrifuge-compatible tubes originally designed to extract saliva from cotton swabs (Salivette system, Sarstedt, inc). The dental sponges were centrifuged at 3300 revolutions per minute (rpm) for 10 min to separate sweat from the dental sponge. Sweat samples were then frozen and stored at -80 °C until they were thawed for analysis. The analysis of sweat samples was conducted by Dresden lab service utilizing a standard ELISA with a 0.2 nmol limit of detection (LOD) and a coefficient of variability of <7% for both the inter-assay and intra-assay measures.

3.4.3 On-Body Cortisol Concentration. Sweat cortisol concentrations were normalized for each participant, and the average value (bar height) and the standard deviation (error bar) of the normalized data are shown in Fig. 4b. We observed average normalized cortisol percentages of approximately 82, 73, 78, 61, and 59 on the aforementioned five locations, respectively. The complete dataset is shown in *Supplementary Fig. 13.*

4 COMBINED PLACEMENT LOCATION ANALYSIS

To visualize combined human factor and biosignals data, we created body contour maps generated by interpolating the sensor data using nearest neighbor multivariate interpolation, and derived a common index associated with the visualizations - SC, HRV, and cortisol contour maps are shown in Fig. 5a-c (The raw data is provided in Supplementary Figures 8-13). Here, red regions signify higher signal quality, and blue regions signify lower signal quality, while dots represent the data collection locations (9 locations for SC and HRV = 6 original locations plus 3 replicated measurements in the opposite arm, and 5 locations for cortisol). To combine biosignals we normalized SC, HRV, and cortisol: $S_{Biosignal,normalized} = \frac{S_{Biosignal,i}}{max(S_{Biosignal})}$. To compound biosignals effects, data were equally weighted: $S_{Biosignals} = w_1 \times S_{SC} + w_2 \times S_{HRV} + w_3 \times S_{Cortisol}$, where, $w_1 = w_2 = w_3 = 0.33$ (Fig. 5d). The user preference body contour map was generated from the design probe study (Fig. 5e). Here, red regions represent higher user preference, and blue regions represent lower user preference. From the raw preference data, we utilized the percentage of approval (Yes) or disapproval (No) for generating $S_{Preference}$. This percentage data was assigned a polarity of positive (Yes) or negative (No). Then, the summation of them was normalized to max of (+1) highest preference and min of (-1) lowest preference. The raw data is presented in *Supplementary Fig. 5* for clarity.

Finally, both human factors and biosignals were balanced to find the optimal wear location using the wear index, $I_{Wear} = w_1 \times S_{Preference} + w2 \times S_{Biosignals}$, as shown in Figs 5f-h. The impact of

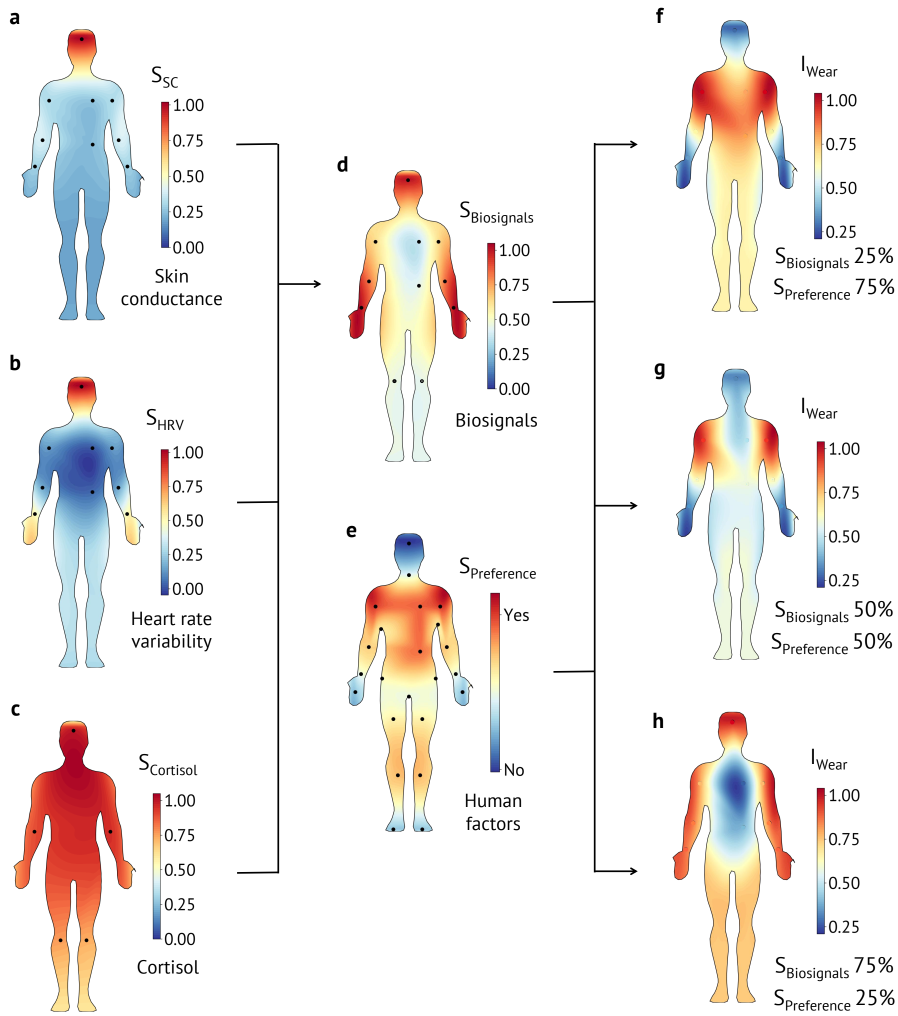


Figure 5: Desired wear locations for a stress management sensor. Higher magnitudes are represented in red, and lower ones in blue. Dots represent places where data was obtained for human factors and biosignal probes (9 locations for SC and HRV = 6 original collections plus 3 replicated measurements in the opposite arm, and 5 cortisol locations). (a-c) Distribution of skin conductance (SC), heart rate variability (HRV), and cortisol. (d) Biosignals ($S_{Biosignals}$) - SC, HRV, and cortisol signal magnitudes are equally weighted to generate the contour map. (e) User preference data ($S_{Preference}$) - positive preference (red), negative preference (blue). (f-h) Combined wear index (I_{Wear}) - high I_{Wear} (red), and low I_{Wear} (blue) with three different weight combinations.(f) heavily weighted user preference $S_{Preference}$ = 75% and $S_{Biosignals}$ = 25% - it is evident that using user preferences, the wear locations are mostly hidden under the clothing on the upper body. (g) both $S_{Preference}$ and $S_{Biosignals}$ are weighted at 50%, which yields forearms and upper arms as desired wear locations. (h) Heavily weighted biosignals $S_{Biosignals}$ = 75% and $S_{Preference}$ = 25% - in this case, desired wear locations move to the extremities, where the biosignal strengths are stronger.

S_{SC} and S_{HRV} on I_{Wear} is discussed in *Supplementary Figure 14*. We used various weight combinations as exemplars (i.e., versus a more systematic approach) to examine the evolution of the wear location based on $S_{Preference}$ and $S_{Biosignals}$. When the preference data is weighted highly at $S_{Preference}$ = 75% and $S_{Biosignals}$ = 25%, the I_{Wear} is high at locations that are generally hidden under clothing (Fig. 5f). In the opposite case, when the biosignals are weighted heavily at $S_{Biosignals}$ = 75% and $S_{Preference}$ = 25%, the I_{Wear} is high at the extremities of the body such as the forehead or the wrist (Fig. 5h). When both user preference and biosignals are balanced at $S_{Preference}$ = 50% and $S_{Biosignals}$ = 50%, a compromise is reached, and I_{Wear} is high on the upper arm and the forearm. Hence, the upper arm or the forearm is the optimal sensing location for our e-skin wearable, where the biosignals are of adequate strength and the location provides privacy to the users.

5 DISCUSSION

Stress impacts our productivity, job satisfaction, and overall well-being [45]. Thus, understanding, measuring, and reducing stress is critical to human health. Our work joins a growing body of HCI literature that covers stress measurement and monitoring using biosignals (e.g., [39]), the impacts of stress on task performance (e.g., [54]), and various intervention technologies (e.g., [4, 60]). The main contribution of our work, and one that can be applied broadly to numerous use cases, is a design process that unifies human factors and biosignal design data to inform sensor placement and other engineering design parameters. Our work corroborates some aspects of prior work on wearable design factors while highlighting specific needs for stress management applications. For example, Zeagler *et al.* developed body contour maps that can be used to inform wearable design and placement, highlighting issues like motion impedance as a limiting factor for PPG sensing [71]. However, these factors were analyzed separately they were focused on general wearable applications mostly for fitness. Factors such as the risk of stigmatization that affect stress management or other mental health applications [21, 52] were not considered. In our study, half of the participants considered perceived judgment by others to be a downside of using a stress sensor. A third were worried that the wearable would distract them from their daily conversations or that would prompt questions from others. Whereas most common health and fitness wearables are worn on the wrists, we observed that our participants particularly cared about the discreetness of the wear location. For instance, exposed body locations such as the face, hands, and wrists were among the locations most disliked by participants because they were perceived as distracting, uncomfortable, and public.

However, when it comes to building wearables, engineers focus their attention mostly on biosignal reliability on different body locations, and less on human preferences. We combine these "parallel tracks" of design by measuring signal levels at human-preferred locations rather than just designing for optimal signal strength. Our findings show a quasi-opposition between human factors and engineering placement options; while the wrist and the forehead are rich for sensing, users tend not to like these locations and prefer more discrete wear locations for privacy, such as the upper arm and torso. Thus, we proposed a visual and simple mathematical weighting mechanism to combine human factors and biosignals in a non-exhaustive manner to inform designs for different use cases. For example, a public health or wellness application, where healthy individuals may prefer not to reveal their stress or mental health needs, may focus more on human factors, choosing for example the upper arm, despite sacrificing some measurement precision. For a medical application, such as relapse prevention for recovering substance-abuse addicts, where control of their stress is paramount, perhaps the ideal location may be closer to the wrist to maximize measurement precision. Thus, this presents interesting challenges and opportunities for communicating this data to users. For example, in applications where discreetness is preferred, taking advantage of alternative devices users may carry (e.g., smartphones, smartwatches, tablets) as displays and intervention sources would be critical to explore.

This combined approach of considering human factors and biosignals is not traditionally used among engineering or psychophysiology researchers. Colleagues from those teams found that designing for human-preferred locations was not a simple task due to many limitations in building the sensors or obtaining data, even with intensive methods, such as the one used to obtain sufficient sweat Cortisol. They, however, found this human-centric design challenge stimulating, forcing them to think harder about how to engineer these sensors. Ultimately, the flexibility to manipulate the weights of our combined index and their visualizations would be useful tools to improve communication across dissimilar teams. Further, there are opportunities to explore adaptive learning of appropriate weights given a use case and a few examples (i.e., similar to [3]). Further, similarities between use cases may allow them to serve as training data for others further lowering barriers to using our method to inform future design.

6 LIMITATIONS AND FUTURE WORK

A systemic limitation was derived from the combination of research practices from three groups of researchers, HCI looking at human factors, chemical engineering looking at on-body physiology biosignals, and psychophysiology looking at efficient cortisol elicitation and measurement from sweat. The main differences lie in cohort sizes. Although the human-centered design cohort (n=24) could be considered small and exploratory, it is customary in engineering and psychophysiology research to use even smaller sample sizes to collect biosignal data, increasing measurement reliability using reproducibility approaches of multiple measurements per participant. That said, future work should aim to further validate our findings by collecting data from larger, diverse samples.

Human factor data may have been affected by novelty effects, acquiescence bias, and participant's prior experience with wearable technologies. A larger sample may help bring more perspectives from participants familiar with wearable devices. While we did not observe any negative reactions to the use of e-skin sensors in public the potential has been noted in other contexts, e.g., e-skins devices for interactions with other electronic devices [48]. Moreover, we derived our questionnaires from specific sections taken from the WEAR Scale [29, 30] to understand elements applicable to a lo-fi prototype; future work could use the complete scale when evaluating higher fidelity prototypes.

Cortisol data was not collected by our wearable prototype, as it did not have a microfluidic solution to extract sufficient sweat. This limitation is not a trivial pursuit to measure cortisol from sweat in the future, and perhaps other methods such as microneedles must be assessed before settling on a viable solution. Furthermore, cortisol was extracted using an intensive method of raising body temperature, to guarantee a sufficient amount of sweat to extract reliable cortisol readings. This limited the places where sweat could be collected, which generated the need for interpolated data to be used for the join Index. Although, for our application, we believe this was a fair approximation, acquiring data from more locations (*e.g.,* similar to [64]) would improve the quality of the body maps shown in this work.

In terms of visualization and index resolution, weighting may need to be adapted based on preferences from specific populations and additional ratios explored to obtain an exhaustive search of all combined possibilities. Furthermore, our preliminary data may not be applicable to non-healthy populations. For example, patients undergoing treatment for health conditions where chronic stress management is relevant, such as recovering substance-abuse addicts, people suffering from chronic mental disorders, or those recovering from cancer, may have different preferences, and different biosignal intensities across the body. Nevertheless, given the analogies between stress management and other mental or chronic health conditions that tend to be stigmatized in society, we believe that our combined method could be applied directly to any wellness, wellbeing, or public health application.

7 CONCLUSION

There is a clear need for new wearable devices that continuously monitor stress in everyday life. With recent advances in electronic-skin manufacturing methods, it is increasingly possible to design *skin-like* devices that are imperceptible, seamless to use, and concealable under clothing, making it easier to continuously measure biosignals in a private and precise manner. While the design of such wearables is mostly based on engineering needs, and less so on human factors, it is important to guide designers and engineers to consider both of these constraints in parallel early in their design processes. We combine human factors with biosignal stress measurements (HRV, SC, and cortisol) into a simple visualization and weighted index method to suggest wear locations. Our system easily adapts to different use cases that may require more or less emphasis on user or system needs. We envision our tool as an aid to bridge the gap between human factors and engineering needs to design e-skin wearables that may require a compromise between signal precision and user factors for a variety of wellness or medical applications.

ACKNOWLEDGMENTS

This work was supported in part by the Stanford Catalyst for Collaborative Solutions and the National Science Foundation SenSE program (grant no. 2037304). We thank Min-gu Kim, Chenxin Zhu, Hongping Yan, Sahar Harati, and Eusha Abdullah Mashfi for the technical discussions and help with the manuscript. Contributions from Y.K., M.L.M., and P.E.P. were made while transitioning from Stanford University to the University of Southern California, the University of Delaware, and the University of Maryland (respectively).

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