Received June 21, 2019, accepted August 16, 2019, date of publication September 11, 2019, date of current version September 25, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2940866

AffectiveWall: Designing Collective Stress-Related Physiological Data Visualization for Reflection

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This work was supported by the Full Ph.D. Scholarship awarded by the China Scholarship Council.

ABSTRACT Excessive workplace stress affects the individual's health as well as social collaborations, so the management of stressors is essential. However, an individual worker who only subjectively reflects on his or her individual and social stressors may misinterpret them, and thus not be able to manage them. This paper aims at engaging workplace stress reflection on objective stress-related physiological data using a shared display, which provides an anonymous view of the individual stress-related physiological signals (i.e., heart-rate variability) through a collective visualization. A minimalist proof-of-concept system is implemented for investigating the design space and deployed during group collaboration. The user study results show that the visualization successfully drew the participants' awareness and increased their understanding of self and organizational stress. This work highlights the importance of objective physiological data in the reflection process of organizational stress management.

INDEX TERMS Organizational stress, stress visualization, reflection, biofeedback, workplace.

I. INTRODUCTION

Nowadays, stress management has become a growing concern for office health. Office workers often suffer from chronic stress caused by, e.g., excessive workload, position changes, unemployment risks. Physiologically, prolonged stress may break the balance of endocrine levels, unbalance the autoimmune system and contribute to cardiovascular diseases. These stress-related factors may also reduce working performance. Beyond the individual stress, organizational stress [1] (collective stress) is another type of stress within an organization or group. Common stressors in an organization could be interpersonal, such as different types of peer pressure and social comparisons [2]. These stressors could highly affect the interpersonal and intrapersonal emotional status, reducing job satisfaction of office workers and weakening organizational competitiveness. Thus, stress management has received extensive attention and has been investigated widely [1], [3]–[5].

As the human physiology reacts to stress, measuring stress-related biometrics and presenting the related information back to the users can facilitate self-reflection on and self-regulation of stress [3], [5], [6]. Some researchers have claimed that the key issue regarding stress management is mirroring the stress to people in order to draw self-reflection rather than finding ways to diagnose the stress [7]. Such tools that help people collect and reflect on their personal information were defined as personal informatics (PI) systems [8]. PI systems emphasize self-tracking and self-reflection. As the whole process is operated by the individual themselves, potential subjective validation bias is inevitable [9] during this self-reflection process [10]. As a result, subjective interpretations of oneself may lead to inefficient self-awareness and biased reflection, which might result in a negative loop and hinder further behavior changes.

People who are situated in a shared context will take others into consideration in the interactions, and regulate themselves in their actions [11]. Therefore, we assume that interpreting PI as a collective in a shared context can help people gain a better understanding of both self and organizational stress. To investigate this assumption, this paper presents a conceptual design, *AffectiveWall* (Fig. 1), a shared visualization that facilitates the reflection of organizational stress by visualizing the individual worker's stress-related physiological signals as a collective.

Fig. 1 shows the example scenario. In the coffee room next to an office, AffectiveWall works as a shared display that visualizes the office workers' stress information over time.

The associate editor coordinating the review of this manuscript and approving it for publication was Feng Xia.

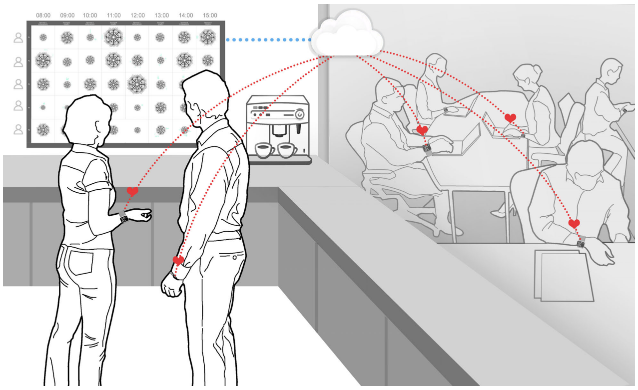

FIGURE 1. Example scenario of a collective stress-related visualization that shows a collection of peers' individual stress. Based on the collective vital signals from the users, an anonymous visualization related to the individuals in their workgroup is shown collectively in the coffee room. People discuss their stress levels with their colleagues during the break.

When colleagues enter the coffee room to take a break from work, they will notice their own and their peers' stress levels and the changes over time. For instance, an employee finds out she is the most stressed person among her peers, and the whole group is under too much stress. This feedback may trigger her to take further actions to manage the underlying stress factors, such as talking to someone. During tea-time, the group members can reflect on their stress patterns and brainstorm what to do after work together.

In the visualization, we mapped the individual's collection of physiological measures of the stress-related index (e.g., heart-rate variability, HRV) to the timeline, aiming to show a collective of the repeated physiological measures from multiple users. To facilitate the users in reading their stress status from the collective visualization, we correlate the stress-related index to the size of the pattern while preserving the time-series information. This allows one to easily compare their stress level in the collection, both inter- and intra-personally. To avoid additional peer pressure induced during the interpretation of the visualizations, all the stress patterns were anonymized. The user can only access their own stress information and a group stress overview; their personal stress information cannot be accessed by others.

The design has been investigated and tested by a series of studies. Results of several exploratory studies identified the parameters for visualizing the stress-related information as a collective. A pilot user study revealed the individual and social stressors, as well as the subjective validation bias found in the self-reflection. We also implemented a proof-of-concept prototype and tested it with 24 participants, and the results showed that the users can interpret their physiological stress status from this collective visualization; they can connect their subjective feelings with their physiological data, they also positioned the self-data in the group and therefore made the reflection from multiple aspects.

The main contribution of this work is the design and the preliminary user experience of a collective stress-related physiological visualization for reflection.

II. RELATED WORK

A. WORK-RELATED ORGANIZATIONAL STRESS

Shirom proposed a facet definition of organizational stress [12] as arising from an employee's perception of an environmental demand which exceeds his/her resources. The stress is conceived to be an interaction, which takes place between an employee and his/her work environment [13]. For the organization, distressed employees who have high job dissatisfaction level and high absenteeism rate will directly lead to poor working performance and will have a negative affect on business benefits. Previous research suggests that workgroup members tend to share moods and emotions [14]–[16]. Unfortunately, this ''emotional contagion'' [17] applies equally to stress [18]. An organizational coping method that encourages the worker to share their emotions without these social contagions is therefore desired.

B. HCI FOR STRESS MANAGEMENT

Personal informatics (PI) and biofeedback systems are commonly-used for stress management. Personal informatics systems, also known as PI systems, is mainly designed to provide users with actionable, data-driven self-insight to help them change their behavioral pattern for the better [10]. PI systems offer insights that are hardly approached by means of observation by the users, such as physiological parameters, which can stimulate users curiosity in knowing themselves better and motivate behavior changes. Li et al. used a five-stage model [8], which described PI systems in five stages: *preparation*, *collection*, *integration*, *reflection*, and *action*, to help people analyze the PI systems and the barriers between each stage. The model also demonstrated that, in PI systems, reflection is necessary before taking action for stress management.

A biofeedback system collects user's bio-signals (such as HRV) and provides these data back to the users in various formats in order to bring the unconscious physiological process under conscious control [6]. It is proven to be an efficient tool for relaxation training and stress management [19]–[21]. Regarding stress management, HRV-based biofeedback, which is related to the users' autonomic nervous activities, is proven to be practically effective [3], [22], [23] and is applied in biofeedback installations [24], [25]. Nonetheless, biofeedback systems are useful only if the users feel they need such kind of relaxation training, and such a need comes from a proper reflection.

C. STRESS-RELATED DATA COLLECTION

Stress can be measured in both physiological and psychological human responses. Physiological stress can be measured when the human brain perceives the stress situation and activates the autonomic nervous system (ANS), which accelerates the heart rate (HR), stimulates the sweat glands, and increases the blood pressure (BP) accordingly [26], [27]. Researchers in the field of affective computing [28] highlighted several biomarkers that could potentially quantify physiological stress, including HRV, galvanic skin response (GSR) [29], HR, BP, etc. HRV is the most commonly used biomarker that can be measured using electrocardiography (ECG) or photoplethysmography (PPG) sensors [30]. Decreased HRV is associated with mental stress [31]. For short-term measurement and analysis, time domain HRV indexes (e.g., SDNN, RMSSD, AVNN, and pNN20) are more robust than frequency indexes (e.g., LF, HF, LF/HF) [32]. Among all, the standard deviation of NN intervals (SDNN) showed a significant decrease in the stress condition [33]–[36], which can be a reliable HRV parameter for quantifying physiological stress.

Sensing physiological stress is more challenging in the collective context because the deployment of biosensors also needs to be scaled up. Contact-based wearable PPG or ECG sensors that achieve accurate timing control and exhibit a high signal/noise ratio could be a more plausible solution. A willing-to-wear and easy-to-wear smart device (e.g., smartwatch) could provide sufficient computational power and wireless connectivity to enable continuous HRV tracking, but it requires the users to wear such a device in the context. We considered contactless solutions such as VitalRadio [37], which is a room-scaled, unobtrusive solution that can track multiple users' HR and respiration simultaneously without requiring them to wear any devices. However, these solutions may not yet be precise enough for sensing HRV in daily scenarios.

Psychological (mental) stress can also be self-reported using questionnaires and scales, such as the STAI (State-Trait Anxiety Inventory) and RRS (Relaxation Rating Scale) [38]. The scalability of measurement can be further improved by turning it into a mobile application. Although it is more practical in the collective context, these personal mental stress data can only be acquired if they are voluntarily provided from the subjects (users), which results in low availability and low credibility [39], especially in a shared context.

D. AFFECTIVE DATA VISUALIZATION

Stress-related data collection can be visualized to enable the users' awareness and engagement. It is considered as a type of personal visualization [40]. Ubifit [41] displays animated activity-related data on a mobile phone's wallpaper to improve awareness of and successfully engage in physical activities. Affective Health [7] provides the user a real-time spiral-like data visualization of biosensor data, allowing him or her to connect these data with his or her daily activities and subjective experiences. AffectAura [42] interactively visualizes multimodal sensor measures and the predictions of the user's affective status with the contexts. Kocielnik et al. [43] also visualize GSR data with a user's calendar events tried to reveal stress with their activities. Affective Diary [44] provided the user sensor data and daily materials (messages, photos, etc.) of past events to evoke reflection. Although some of the systems (e.g., [7], [43]) visualizes stress-related affective data, these are personal visualizations for self-reflection.

Based on the common theory that social influences are capable of achieving higher actionability and engaging behavior change, the recent trend of self-revelation systems shifted from personal devices to applications in a social context. Miro [45] is a system that shows an office building's collective emotional climate through an ambient dynamic painting in a public visualization for occupants to develop a sense of emotional climate, but it failed to transfer the information correctly to its audiences. FriendSense [46] uses the 'technical probe' method to investigate the relationships and activities that constitute a group of colleagues at work. Although the expressions did not fully afford the users emotional expression, they did contribute insights into visualizing self-report data collectively in a public setting. MoodJam [47] is an online platform where users can log in to record their mood multiple times a day and get access to look at other people's data and the history of themselves. MobiMood [48] is a mobile application that allows users to share mood with friends and discovered that curiosity about peers' whereabouts and activities is part of human nature. Moodlight [49] displays the individual or a pair's arousal state using an ambient display by different colors of light. Although these systems visualize affective data in a shared context, there is no or only a weak correlation between these data visualizations and stress management.

E. REFLECTION ON STRESS

Reflection was defined by Baumer et al. as ''reviewing a series of previous experiences, events, stories, etc., and putting them together in such a way as to come to a better understanding or to gain some sort of insight'' [50]. Reflection is often described as a motivation for providing increased self-knowledge for work in both health and personal informatics [50]–[53], and seen as an approach to promoting greater awareness and learning to self-manage chronic conditions [54], such as stress [7], [55].

However, subjective confirmation biases are pervasive during self-reflection [56]. People tend to seek and interpret evidence that aligns with their existing beliefs [9]. In this case, misinterpreting stress among individuals may account for inefficient employees and deteriorating relationships [57]. Group reflection could be beneficial for people to discover a phenomenon which is sometimes difficult to observe individually or subjectively [51], [58], [59]. In this case, the individual bias can be explicated and adjusted from multiple perspectives through conversations [50]. Nonetheless, social pressure, which may affect group reflection, should be avoided.

F. SUMMARY

In HCI, stress management can be realized through personal informatics and biofeedback systems. However, reflection is the necessary stage towards taking action — stress management. The current PI system supports self-reflection; however, self-reflection inevitably exhibits subjective validation bias [60], as one will consider a statement or another piece of information to be correct if it has any personal meaning or significance to oneself. Problems that occur in the reflection stage will disable further action [8] — in this case, stress management. For example, unrealistic self-expectations may lead to a biased self-reflection, and even worse, may incur extra pressures on oneself. To avoid biased self-reflection, we should consider the reflection process in a shared context, as people will take others into consideration in the interactions, and regulate themselves in their actions within the shared context [11].

III. DESIGN AND IMPLEMENTATION

This section first describes the design considerations based on the related work. Then we describe the design of AffectiveWall, a collective visualization for workplace stress management following the five stages of the PI model.

A. DESIGN CONSIDERATIONS

Based on the findings of the related work, we consider that the design of visualizing individual stress in a collective context should meet the following three criteria: *validity of collection*, *readability of integration*, and *stress-free of reflection*.

- *Validity of Collection.* The design should depict the individual's and group's stress status meaningfully with valid stress markers. Only when the validity of the data collection is mapped with the ground truth can the data integration be meaningful for themselves and their community.
- *Readability of Integration.* The design should clearly integrate the individual stress data and group stress data for the users at a glance, which is especially appreciated by the office workers in the workplace scenario.
- *Stress-free of Reflection.* The design should not bring extra stress among the users during the interpretation and discussion. Only when the experience is stress-free can the users comfortably share their status and feelings with each other and this is more likely to trigger further actions on stress management.

B. DESIGNING COLLECTIVE STRESS-RELATED VISUALIZATION

We aim at designing a collection of stress-related visualization in a shared context, such as a workspace. The primary design challenge is how to enable the workers to make meaningful inter- and intra-personal comparisons without incurring additional peer pressure.

1) DESIGN

Regarding *validity of collection*, we use the HRV as an objective physiological stress marker. The inter-beat interval (IBI), which can be precisely computed using a conventional PPG or ECG sensor and a micro-controller preloaded heartbeat detection algorithm, is used in this installation. The *validity* of the data collection is based on the assumption that an infrastructure of continuous collective HRV sensing, data

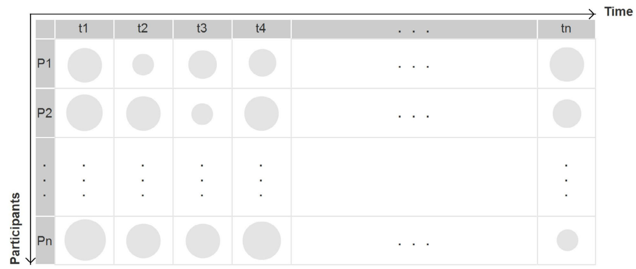

FIGURE 2. Example spatial arrangement of stress patterns in 2D. X-axis: time. Y-axis: anonymized individuals.

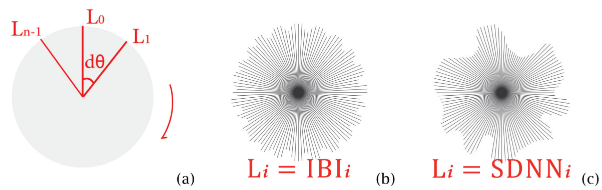

FIGURE 3. Single-layered patterns. (a) Model representation. (b) P_{IBI}. (c) P_{SDNN}.

collection, and the network-connected public display exists as shown in Fig. 1. Regarding continuous sensing, the sensor should be made into a wearable form so that the measured data can be collected continuously. Such an infrastructure can be realized by requiring each worker to wear a network-connected PPG-sensing device, which can reliably monitor the user's HRV in the background of their everyday activity and periodically synchronize the HRV data to the Cloud server, and thus the data visualization can be realized on the network-connected public display.

Regarding *readability of integration*, to enable meaningful inter- and intra-personal comparison, we intend to map the individual's HRV patterns onto a timeline so that the stress from different people that happened at the same time is comparable. Fig. 2 shows an example 2D view of stress-related visual patterns, where the x-axis represents the timeline and the y-axis represents the participants. In this view, a user could backtrack his or her historical stress status and compare his or her stress status with others, and further observe the group stress through the overview.

For the pattern design, we first considered a fixed-duration (e.g., 5 minutes) discrete measurement for simplicity. We want to preserve the time-series HRV history for reflection, and therefore designed the following three minimalist patterns: P_{IBI}, P_{SDNN}, and $P_{SDNN+Ring}$.

P_{IBI}: The IBI data collected from the PPG sensor were mapped to the angle and length of lines, which were then arranged clockwise as a round pattern. The θ of the n-th data in the pattern was set to $\theta = n \times \frac{2\pi}{N}$, where N was the total number of data. The length l of a stroke was mapped to IBI (Fig. 3b). In this case, integrating a huge amount of data in a round pattern allowed for a clearer view and easier comparison.

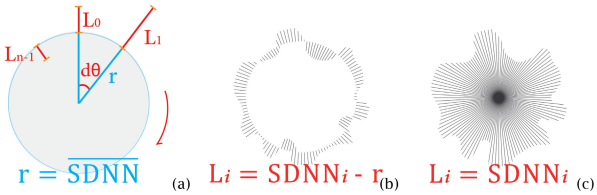

FIGURE 4. Single-layered patterns enhanced by $\overline{SDNN}$. (a) Model representation. (b) $P_{SDNN+Ring}$. (c) P_{SDNN}.

P_{SDNN}: To map the HRV to the size of the pattern, the length of each stroke was determined by $SDNN16$, Windowed (W = 16) Standard Deviation of inter-beat (NN) intervals. The $W = 16$ was chosen because it is large enough to include at least one complete respiratory circle and small enough to be sensitive to changes in breathing pattern [61] (Fig. 3c and Fig. 4c).

$P_{SDNN+Ring}$: The mean SDNN, $\overline{SDNN}$, which could represent the overall HRV during the measurement, should also be mapped to size. Therefore, the $P_{SDNN+Ring}$ model (Fig. 4b), which had an additional overlaid circle was designed to enhance the readability of the overall stress of the P_{SDNN} pattern.

Regarding *stress-free of reflection*, peer comparisons commonly existed, and the personal information shown in a smaller workgroup could also lead to peer pressure. Therefore, we applied anonymity [62] to avoid extra stress from these social factors. The visualization did not reveal personal information, such as names. Instead, different avatars were shown on the screen so that the users could recognize the differences between individuals data. Every user held the identity of his or her avatar privately (e.g., through their personal devices), therefore each user knew his or her data but did not know the identity of the others, just as the others did not know which data was from the user. The identity of the avatars could shuffle periodically (e.g., daily) so the users could prevent others from knowing the ownership of an avatar.

2) EXPLORATIVE STUDY

Two online questionnaires were used for understanding how effective the users perceived different types of stress visualization to be. Questionnaire 1 tested whether the P_{IBI} pattern or the P_{SDNN} pattern design was more accurate in presenting the stress-related data. Questionnaire 2 tested whether the additional information $P_{SDNN+Ring}$ could help judgment of the stress level. The questions were generated using a database of 14 users' 3-minute IBI data, none of whom had a missing beat. We first ranked these data using their $\overline{SDNN}$ value from the highest to the lowest, generated their P_{IBI}, P_{SDNN} and $P_{SDNN+Ring}$ patterns accordingly, and separated them evenly into two smaller sets, A and B, as shown in Fig. 5. The seven patterns in each group were used for generating 21 single-choice questions, in which the participants need to identify which one was more stressful. Fig. 6 and 7 show examples of the questionnaires' questions. The order of each question was within-subject randomized. The question sets A and B were between-subject counterbalanced. The participants of the two questionnaires were recruited separately. Both questionnaires were answered online.

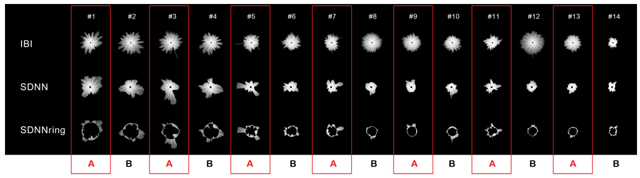

FIGURE 5. Database of 14 participants' 3-minute IBI data. P_{IBI}, P_{SDNN}, and $P_{SDNN+Ring}$ patterns were generated and categorized into two groups based on the ranking of $\overline{SDNN}$ from the highest (left) to the lowest (right).

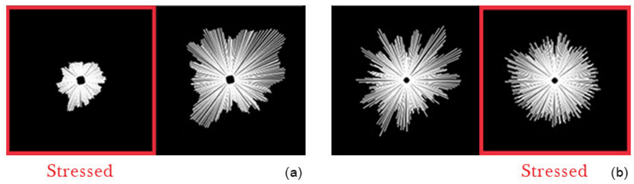

FIGURE 6. Example questions of Questionnaire 1: Choose the more stressful pattern in (a) P_{SDNN}. (b) P_{IBI}. Correct answers are indicated in red.

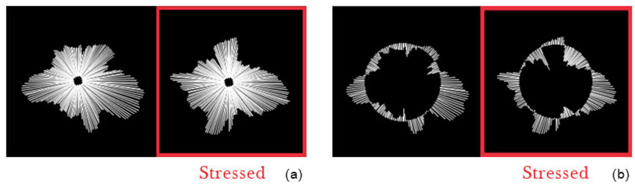

FIGURE 7. Example questions of Questionnaire 2: Choose the more stressful pattern in (a) P_{SDNN}. (b) $P_{SDNN+Ring}$. Correct answers are indicated in red.

3) RESULTS

Questionnaire 1 (Q1) received 31 (19 females, 12 males) responses. The results show that, generally, P_{SDNN} patterns (93.65%) have higher accuracy than the P_{IBI} patterns (78.04%) without a statistical significance (p = 0.265). If we only consider questions with more than two-rank differences, the accuracy of P_{SDNN} patterns does have significantly higher accuracy than the IBI patterns (p = 0.013). The results suggest that the SDNN pattern significantly improves the readability of stress levels.

Questionnaire 2 (Q2) received 36 (21 females, 15 males) responses. The results show that $P_{SDNN+Ring}$ patterns have higher accuracy (95.87%) than P_{SDNN} (91.75%), though, there is no significance found in either overall or any combinations of subsets between these two groups.

User feedback reveals what people think about these patterns. The shape of the P_{SDNN} did interfere with the user's choice, for example, *"The more asymmetric they seem, the more stressful they appear to me."*(Q1P30). *"If it had one line that was farther out than others that bothered me more than the smaller ones"*(Q1P14). Some mentioned

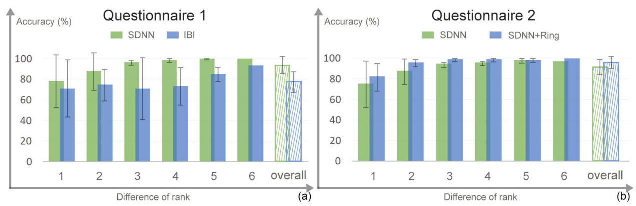

FIGURE 8. **Questionnaire study results. (a) P_{IBI} vs. P_{SDNN}. (b) P_{SDNN} vs. $P_{SDNN+Ring}$.**

that the ring could increase the accuracy of their judgment, *"I think the ring size was most clear to me"*(Q2P35), while some mentioned that the ring makes the $P_{SDNN+Ring}$ shape *"visually clearer because of the circle but less interesting"*(Q2P14). Some participants felt an emotional connection because the patterns are visualized from real heartbeat data, for example, *"I would like to have a ring of my own heart"*(Q2P36). *"Mainly curious whether these visualizations are based on real heartbeats and curious what mine would look like!"*(Q2P31). About the mappings, although most of the participants did it correctly, some participants thought the visualization counterintuitive. For instance, *"I would expect that the bigger, flexible flowers would present more stress"*(Q1P20), *"I feel more stressed when I see bigger rings"*(Q2P19) and *"For stress, my intuition says that small means good, whereas big means bad."*(Q2P32).

In sum, we conclude that both P_{SDNN} and $P_{SDNN+Ring}$ patterns did provide better readability than the P_{IBI} pattern. An overlay of ring further improves the readability of the overall stress level. It concurred with the visual perception theory that size is more salient than shape [63].

IV. PILOT STUDY: UNDERSTANDING USERS

The *pilot user study* was deployed to understand how the office workers reflect on the stress that they encounter everyday.

A. METHOD

An exploratory semi-structured interview was conducted to better understand how the office workers reflect and cope with stress in a workspace. Participants in the interview were 25 Ph.D. students [64] in a university in the various fields in design, engineering, and architecture. This target user group was selected because their self-capability was either too low or too high for the job requirement [65]. The sample involved 13 females and 12 males, and the nationality ranged from nine countries including Asia, Europe, North America, and South America.

The interview aimed to explore the main factors that elicited stress during their daily research life and how they cope with that. A semi-structured questionnaire was designed to evoke participants' recall of their stressed moments and the factors associated with them. For instance, questions like *"Please describe a stressful moment of your research life."* and *"Where do you think your stress comes from?"* were asked and recorded during each interview. The preference of self-stress management methods to conquer stress in daily life were also asked about at the end of each interview. The process of all the interviews was recorded and transcribed by the first author into text. Afterward, the transcriptions were analyzed by Dedoose,[1] a qualitative data-analyzing tool. To make sure the results were objective, two people were invited to encode the data independently. After coding, the two coders presented their coding results to each other and made a tree diagram to categorize the main factors of the results together.

TABLE 1. **Frequency of mention (Unit: Head count).**

Individual	#	Social	#
Multitasking	25	Contagion	21
Procrastination	22	Misunderstanding	14
Deadline	17	Expression	11
Unmet expectation	16	Comparison	8
Time management	13	Judgement	6

Other individual stressors: Task management (12), Distraction (12), Perfectionist (10), Uncertain target (10), Uncertain future (9), Ideality and reality (5), Input and output (4), Financial pressure (4), Low productivity (3), Uncertain knowledge (2)
Other social stressors: Disagreement (3), Loneliness (3)

B. RESULTS

Table 1 shows the frequencies of mentions, which are classified into two categories, *individual* and *social*, and ranked by the head counts. The top three mentions are: multitasking (100%), procrastination (88%), and contagion (84%). *Individual* stressors are mainly about time and task management, unmet expectation and uncertainty. For example, *"I always think about other tasks when I am doing one. The more worried I am about it, the worse it will be."* (multitasking), *"I feel that I can be better if I start earlier, but sometimes when I realize I still have some time, I just don't want to start right now."* (procrastination). *"Panic! The results of the experiments are not as good as I expected."* (unmet expectation). *Social* stressors also received considerable mention. Social contagion, bad communications, and peer comparison are the main reasons that caused stress. For example, *"I think when you see people who are very stressful, I wouldn't know how it's gonna affect me but it will certainly change the mood in the room"* (contagion); *"When I see my colleagues have excellent work, I'll question myself why I have not"* and *"When I see other people can handle five things simultaneously and I can't, I feel sad that I don't have that ability"* (comparison); *"I was like already doing many things, but he wasn't aware of every detail*" (disagreement).

Subjective validation bias does exist in their self-reflection, as they are trying to find the reason for their subjective speculations. For example, *"I think now that a big part of the environment is not that stressed. I think about my colleagues who are in the same program. They tend to be more stressed because they're going to write their thesis and maybe if they*

[1] https://www.dedoose.com/

are in my office, that would definitely change the mood of it.", "*He probably thinks I'm such a stupid student.*", and "*Sometimes the girl in the room is very stressed, and I would think 'Oh, what's going on?' But later I would say, 'Oh it's probably her problem'.*" In fact, these speculations are impossible to be made objectively.

Overall, the results confirmed that the existences of social stressors and subjective validation bias self-reflection.

V. FORMAL USER STUDY

A *formal user study* was designed to understand the user experience of this collective visualization for reflection.

A. EXPERIMENT DESIGN

1) PARTICIPANTS

Twenty-four participants (11 females, 13 males) aged from 27-42 (M = 30; SD = 3.51) were recruited for the study. They were separated into six groups of four. All group members were required to be colleagues to simulate a daily workplace scenario. Each group was further divided into two subgroups so that the two participants could team up and collaboratively compete with another team formed by the other two. Such minimalist group settings were also beneficial to evoke an efficacious conversation [66].

2) APPARATUS

To simulate the usage scenario that we visualized in Fig. 1, a room was prepared to simulate a working space. Four laptops were prepared for each participant (P1, P2, P3, P4) in front of four chairs. A mouse was connected to each computer for standardized one-handed input. The participants used these computers in performing collaborative tasks. Aside from each laptop, a PPG sensor (Fig. 9) clip was fixed on the desk surface for measuring participants' HRV. The placement of the clip positioned the hand in a comfortable way for noiseless signal collection.

Each of the PPG sensors was attached to a customized operational amplifier with adjustable gain, which allowed the users to adjust the sensitivity of PPG sensing by turning the knob on the potentiometer. The beat detection algorithm was realized using the comparator circuit in this hardware design. Each module was connected to a PC through an Arduino Uno board mounted an ATMega328P microcontroller, which sampled the PPG data and the detected beats in 500Hz and sent the readings to another computer through the USB serial port. The IBI, $SDNN16$, and $\overline{SDNN}$ were calculated from the collected data and visualized on the screen in real time.

Regarding visualization: we realized the previously proposed patterns and spatial arrangement and displayed them collectively on the wall through a projector (Fig. 10a). The projector was hidden beneath the office desk and projected directly on the wall facing to the group members. The pattern was drawn in mint green for $P_{SDNN+Ring}$, all the $SDNN16$ that were smaller than the $\overline{SDNN}$ were pointed inward and emphasized in a darker color to make the ring easier to

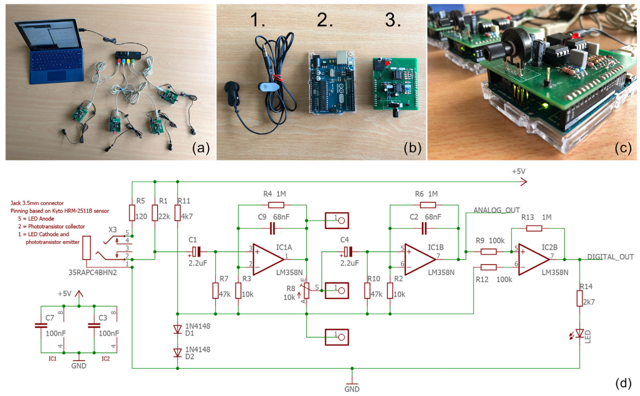

FIGURE 9. Hardware apparatus. (a) Overview. (b) Each module consisted of 1) a PPG sensor, 2) an Arduino board and 3) an operational amplifier that allows for senstivity adjustment by (c) turning the knob. (d) Schematics [67].

FIGURE 10. User study. (a) Apparatus. (b) Results of $P_{SDNN+Ring}$. (c) Results of P_{SDNN}.

observe. Pressing a button could toggle the display between the P_{SDNN} and $P_{SDNN+Ring}$ patterns.

3) TASKS

The tasks aimed to change the stress level of the participants and show them the change in their stress patterns afterward. Math challenges were used to increase their stress level by extending their mental efforts [68]. Before each challenge started, participants were asked to do paced deep breathing with a peaceful video to reduce their stress level (task 1 and task 3). In task 2 and task 4, each participant in the two teams, [P1, P2] and [P3, P4], collaborated with his or her teammate to compete with the other team. Both sides were asked to solve the math challenges on the same shared Google spreadsheet so that everyone could see each other's progress. To motivate them to do their best, participants were informed that the winning team, i.e., the team with the most completed and correct answers would win an additional 5 euro voucher.

Two types of collective stress [69] were introduced in the team: 1) All stressed: aimed at making all the group members feel stressed, and 2) Some stressed: some members stressed while some are not. In the *All stressed* condition (task 2), both teams did a long list of two-digit multiplications (e.g., $79 \times 94 = ?$). In the *Some stressed* condition (task 4), P1 and P3 did the easier two-digit addition (e.g., $58 + 97 = ?$) while P2 and P4 did the same two-digit multiplication so that unequal tasks may cause different uneven stress levels within the groups. Every team experienced *All stressed* before *Some stressed* to avoid the uneven stress also happening in the *All stressed* condition.

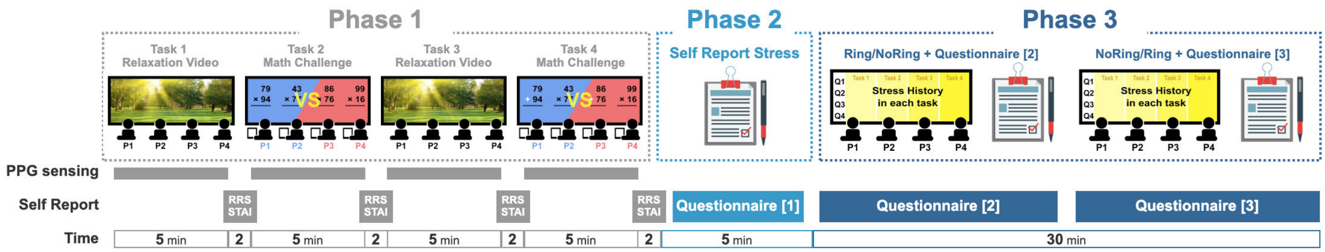

FIGURE 11. **User study procedures.**

4) PROCEDURES

Fig. 11 shows the procedures of the whole study, which includes three phases which last for approximately 60 minutes in total. In Phase 1, which was started after the participants received the introduction, the participants were asked to finish four 5-minute tasks. After each task, the participants were asked to complete two self-report stress questionnaires (RRS and STAI). In Phase 2, participants were asked to reflect on the four tasks in Phase 1, and rate their subjective stress level on each task on a 5-point Likert scale (1: very relaxed; 5: very stressful) in the Questionnaire 1. In Phase 3, each participant P_i got his or her identity of *avatar* Q_i, where $Q_i \neq P_i$, which indicated the data ID (row number) in the anonymized stress visualization. Then, the stress visualization was shown to them in patterns of P_{SDNN} or $P_{SDNN+Ring}$, and the participants were asked to fill questionnaires 2 and 3, respectively. In these two questionnaires, the participants were asked again to rate their stress level on a 5-point Likert scale based on what they read, and further *rank* their relative stress level (1: I am the most stressful one; 4: I am the least stressful one) in their group. They also gave comments on the usefulness of anonymity, reasons for their rankings and ratings, and reflections of the tasks with the visualization. During all three phases of the user study, verbal conversations were not allowed in order to reduce the extra pressures from social interactions. Nonetheless, after the participants were told the study was over, and they could freely choose to leave or stay for an optional discussion, in which our observation continued. The study paid each participant 20 Euros as compensation.

5) MEASUREMENTS AND DATA ANALYTICS

Regarding objective measurements, we measured each participant's IBI data, which were used for quantifying the stress level by calculating the SDNN. To understand the validity of the SDNN data, beat miss rate R_{miss} was calculated from the uncleaned raw data using the following procedure: 1) calculate the median Mdn_{IBI} of all N_{IBI} IBIs collected in the session. 2) convert each IBI_i into equivalent missing beat count $N_{miss} = round(\frac{IBI_i}{Mdn_{IBI}} - 1)$, and 3) obtain $R_{miss} = \frac{N_{miss}}{(N_{miss}+N_{IBI})}$. The $SDNN16$ and $\overline{SDNN}$. For the calculation of SDNN, we first excluded the IBIs which $N_{miss} > 0$ and then calculated the rest of the $SDNN16$ and $\overline{SDNN}$ using the methods mentioned above. Regarding subjective measurements, the rankings and ratings in the three questionnaires were used for quantitative analysis. The comments, reasons, and reflections collected in the RRS, STAI, three questionnaires, and the post-study discussions were also used in understanding the user experiences.

B. QUANTITATIVE RESULTS

This session describes the quantitative results in terms of our three considerations: validity of collection, readability of integration, and stress-free of reflection.

1) VALIDITY OF COLLECTION

The validity of the SDNN-based data collection was examined using the beat miss rate and the comparison of the SDNN calculation between our method and Kubios,[2] a software for clinical HRV data analysis. In all 24(participants)×4(tasks) = 96 5-minute HRV measurements, the results of the Shapiro-Wilk test indicate that the distribution of the beat miss rate is not statistically normal ($p < 0.05$). The median of the beat miss rate is 0% and the mean beat miss rate is 0.4% ($SD = 1.3\%$). The results show the validity of the IBI data obtained from the measurement. For the $\overline{SDNN}$ calculation, the results of the Shapiro-Wilk test indicate that the distribution of differences between our method and the Kubios is not statistically normal ($p < 0.05$). The median of differences is 4.98ms, and the mean difference is 7.53ms ($SD = 7.74ms$). The results show the validity of our SDNN-based stress-related data collection.

The validity of tasks was examined based on the responses to the RRS and STAI, and the SDNN calculation. Regarding the RRS, the results of a repeated measures ANOVA with a Greenhouse-Geisser correction shows that the RRS scores have an effect ($F(1.492, 34.312) = 10.341, p = 0.005 < 0.01$). Results of pairwise t-test further indicate significant differences between task 1 and 2 ($p = 0.012$), task 2 and 3 ($p = 0.02$), and 3 and 4 ($p = 0.037$). Regarding the STAI, the results of a repeated measures ANOVA with a Greenhouse-Geisser correction shows that the STAI scores have an effect ($F(1.447, 33.273) = 7.880, p = 0.005 < 0.01$). Results of pairwise t-test further indicate significant differences between task 1 and 2 ($p = 0.022$) and task 2 and 3 ($p = 0.004$). However, task 3 and 4 have no significant differences

[2]https://www.kubios.com/

TABLE 2. Mean error and standard deviation (SD) of the ranking on the SDNN+Ring and SDNN patterns.

Mean Error (SD) of Ranking Results					
$Type\backslash Task$	1	2	3	4	Overall
$P_{SDNN+Ring}$	0.083 (0.295)	0.250 (0.442)	0.083 (0.282)	0.292 (0.588)	0.177 (0.110)
P_{SDNN}	0.250 (0.590)	0.250 (0.565)	0.167 (0.408)	0.292 (0.624)	0.240 (0.095)

($p = 0.382$), showing that the *some stressed* condition is less stressful in general. The results show that the math challenges did increase the mental stress level.

Regarding physiological stress data, we first exclude the SDNN data of 6 (out of 24) participants, who have at least one task with $>$ 1% beat miss rate, and use the remaining 18 participants' data for understanding the effectiveness of the tasks. The $\overline{SDNN}$ is calculated using Kubios with a medium filter of artifact removal. Results of a paired t-test show significant differences in the $\overline{SDNN}$ between task 1 and 2 ($t(17) = 2.98, p = 0.008 < 0.01$), task 2 and 3 ($t(17) = -3.12, p = 0.006 < 0.01$) and between task 3 and 4 ($t(17) = 3.28, p = 0.004 < 0.01$). The results show that the relaxation and the math challenges also changed the physiological stress level.

2) READABILITY OF INTEGRATION

The readability of the visualization was examined based on the within-group ranking in both the calculation of $\overline{SDNN}$ calculation and the responses of "Please rank your stress level in this group based on the visualization" in questionnaires 2 and 3. Overall, the mean accuracy of $P_{SDNN+Ring}$ (83.33%) is higher than the P_{SDNN} pattern (79.16%) without a statistically significant ($p = 0.983$). If we consider one-rank error as correct, then the mean accuracy increased to 98.96% and 95.83% for $P_{SDNN+Ring}$ and P_{SDNN} respectively. The results show that participants realized the stress level within the group from the visualization. Table 2 shows the ranking results compare with the ranking based on the calculated $\overline{SDNN}$. 22 (out of 24) participants also agreed that they can see the stress level changes with time.

After seeing the visualization, the users significantly changed their perspectives about their stress level regarding the group. The Pairwise t-test shows that the subjective rating in Questionnaire 1 was significantly different from the ratings in Questionnaire 2 and 3 after they saw the $P_{SDNN+Ring}$ ($p = 0.026 < 0.05$). The subjective rating is also borderline significant than the P_{SDNN} ($p = 0.069$). The significance suggests that considering only one type of measures only shows partial stress status, which has inevitable subjective validation bias. Therefore, an additional insight of physiological signals could help the users in understanding their physiological stress and to further reflect on their subjective feelings.

3) STRESS-FREE OF REFLECTION

From a 5-point Likert-scale question during the reflection stage in questionnaires 2 and 3, the mean score of the response "You feel less stressed because the visualization is anonymous" is $M = 3.625(SD = 0.77)$. Fifteen (out of 24) participants (strongly) agreed this anonymous visualization did not add extra pressure to themselves. The mean score of the response "I would feel more stressful if the visualization was not be anonymized" is $M = 3.625(SD = 0.82)$. Sixteen (out of 24) participants (strongly) agreed that they may feel stressed if the visualization is not anonymized. The results showed the usefulness of anonymity during the reflection stage.

C. QUALITATIVE RESULTS

This section describes the qualitative results from the optional discussion at the end of the study. The descriptive conversations about the study setting, the visualization, and the reflection had been recorded, transcribed, and labeled into discrete categories using content analysis approach [70]. The results are listed as follows.

1) SELF REFLECTION

Individuals still make self-reflection individually, but they do the reflection with the objective data provided. Most people express the consistency between their physiological signals and their subjective feelings, for instance, "*So accurate! It exactly the same as my personal feelings! I feel stressed when I was doing the math and especially the last task, people on my left and right were all faster than me made me feel extremely stressful*"(G1P1). On the contrary, two participants find the visualization is opposite to their subjective feelings. For example, "*I'm quite confused about the results. I meditate regularly every day. So I know how I perform when I do meditation. The measurement is the opposite with how I feel. If it is opposite, that would be perfectly accurate, because I know. I can really feel that I can make myself relax*"(G3P2). Notably, the most stressful participants always reflect on their position in the group, for example, "*I am the most stressful one! I am the most stressful one!*"(G4P3) and then either argue with the results or obsess with it and try to find the reasons behind it.

Individuals start positioning their reflection in a group context. Many are more interested in sharing their feelings and discuss with others, such as "*I'm willing to share with others.*"(G5P1) and "*That's very interesting, the program, I already start to think does anybody knows who I am. I don't mind actually sharing. Can we share? Can I tell them who I was?*"(G5P3). Nonetheless, a few people prefer to keep it as private information to themselves, for instance, "*I don't want to let everyone knows my stress level, I feel ashamed of it*"(G3P4). Also, some people mention that they would like to share if they are not the most stressful one. "*If I'm not the most stressful one, I don't mind anonymity. But, if I am the most stressful one, I don't want it to be seen by others*"(G4P4, G5P4).

2) GROUP REFLECTION

Participants among the group reflect on specific individual data or the group as a whole with each other.

Group members reflecting on individual data indicates that people in the group get interest in exploring other people's data in their community. For example, "*It may be fun to discuss each other's stress pattern*"(G5P1). "*Oh, look, P4 is very stressed! Who is P4? P4 definitely needs a vacation!*"(G6P3). And a conversation happen in Group 1: "*A: Who was P4? B: Me! A: Oh, you're really stressed. B: I know, but I don't feel that much stressed at all. I did deep breathing during the video. I don't know why? C: Probably you're doing it in the wrong way. B: What do you mean in a wrong way? C: It is possible that stressful deep breathing would make you more stressed. Then probably normal breathing during math would perform better.*"(G1). In these quotes, group members make reflections on an individual's data and even think about relaxation interventions to help each other. Even more, some groups further reflect on the group data as a whole. Only two groups (G4 and G5) approach group-reflection on group-data. "*Are these (results) normal? Can we see other groups's data?*" (Show her the data from group 3.) "*OMG, that is so big. I feel our group performs better. The other group looks so abnormal*"(G4P2). "*What do the other groups look like?*" (Show her G3, G2 and G1) "*Wow, that looks very different!*"(G5P1). This evidence supports that the group reflect on their performance as a whole to upgrade to a new level of reflection.

3) REFLECTION ON TIME

Some participants try to reflect on what happened during this task and how it mapped to their current stress. For example, "*The reason why I felt so relaxed was because I was tired of watching that boring (relaxation) video*"(G1P2); "*My last session was the most relaxed because I knew your challenge was very difficult and mine was very easy. The moment I saw my math was the addition, I felt relaxed*"(G1P4); "*I think I was still thinking about those multiplication tables in my mind, even though I actually closed my eyes during the (relaxation) video, that's why it shows up like that*"(G5P3).

4) REFLECTION ON PHYSIOLOGICAL DATA

Some users mention that the visualization of physiological data is helpful for self-reflection, such as "*I think I know my stress level better from the visualization*"(G1P1); "*I think the insight can help me reflect on my tasks and corresponding mental stress, and modulate my own preparation and stress-handling better*"(G5P3); "*I think I prefer to compare the ring with myself, like I can see my stress change over time. I can see that during four sessions my stress is already different*"(G5P2); "*It shows that in the last task I'm not stressed. It said my stress is similar while doing the math and when I watch the video. I started wondering if my feelings not that accurate*"(G6P1). This also indicates that participants combine their physiological data with their subjective feelings for reflection.

5) SUMMARY

The results show that the visualization enriches the reflection, and evokes more inter- and intra-personal reflection on stress. Based on the results, the participants reflect on the data history, take other participants into account, and further share their opinions with each other.

The results show that the tasks have changed both the mental and physiological stress levels of participants with statistical significance, and the visualization has significantly changed the participants' subjective perception about their stress level. Interestingly, only 2 out of the 24 participants questioned the authority of the visualization and felt the visualization was inaccurate; on the contrary, most of the participants can make sense and reflect on the visualization to some extent. This finding is in line with Synder et al. [49]. Although our system does provide sufficient validity, we do not wish to claim that our system is the ground truth of physiological stress. Instead, we want to highlight the fact that such an ambiguity between subjective and objective stress could be useful in engaging people in communication and therefore increase the mutual understandings among the members in the group, as discussed in [71].

VI. DISCUSSION

This section discusses the limitations and future work. We first discuss the remaining barriers of AffectiveWall using Li et al.'s five-stage Personal Informatics (PI) model [8]. Then, we discuss ethical issues such as data misuses by the employer, identity disclosure in anonymity, and the potential disclosure of HRV-related diseases. Finally, we discuss the design issues for future work to conduct longitudinal studies to understand how daily stressors affect experiences.

A. REMAINING BARRIERS IN THE FIVE-STAGE PI MODEL

According to the five-stage model of PI system (i.e., *Preparation, Collection, Integration, Reflection, and Action*), problems occurring in each stage would turn into barriers that prevent users from moving on to the next stage [8]. This section outlines the limitations when collectively positioning the five stages of PI in a collective context and discusses how to address them in future work.

1) PREPARATION STAGE

In the preparation stage, the barrier is for the users to decide what data to track and which tool to use for tracking [8]. Our research bypassed this phase by asking the study participants to adopt our system directly. Therefore, we did not examine whether they have the intention of choosing our system as their solution. Further questions are: What data are necessary and valuable for the users? Who would benefit from this system? What could be the effective incentives that would encourage them to contribute their data to the system? These questions should be better communicated to the users.

2) COLLECTION STAGE

Barriers in the data collection stage are mainly *user-related* or *tool-related* [8]. Regarding the *users*, in this study, we obligated people to contribute their data in a short, fixed duration (one hour). As an extended time for data collection is required for a longitudinal study, future work should consider the mechanism to engage the users in contributing data continually.

Regarding the *tool*, the current implementation individually collects users' HRV data through PPG sensors via a USB wired connection, which is reliable and practical in proof-of-concept lab settings. Nonetheless, even when the study participants were well-instructed, and the study was carefully designed to allow for single-handed performing of the tasks, unconscious motion artifacts that affect the PPG signal quality were still observed. Moreover, the sensing and data collection method is still too obtrusive for the users in their everyday activities. To generalize this concept to the workplace in our daily life, the sensing method could be improved by using more unobtrusive and portable sensors, such as wearable ECG sensors [72] with a wireless data collection mechanism.

Instead of HRV, there are other objective measurements of stress [73] that can be collectively sensed in unobtrusive and continuous ways. For instance, heart rate and breathing patterns can be measured using radar sensors [37]; voice can be measured using microphones; and facial expressions can be measured and recognized using a camera [74]. Nonetheless, as well as the reliability issues and how strong these features relate to the participant's physiological stress, the data collection should concern social acceptance, preserving privacy and sensor deployment. These participants should be well-informed regarding these. Otherwise, these sensors may incur additional unpleasant stress for the participants even though they are unobtrusive.

In addition to the objective measurements, subjective measurements can also be collected by smartphone apps [75] or wearable self-reporting devices [76] to facilitate reflection in a later stage [44]. A visualization that combines both objective and subjective measures of stress can provide a more comprehensive overview for further reflections.

3) INTEGRATION STAGE

Barriers in this stage prevent users from integrating the collected social data into an understandable format that can be reflected upon [8]. The challenges of integration in the collective stress context are mainly related to *more stress-related markers*, *a longer time scale*, and *visualization for a larger group*. In this work, we use only one stress-related physiological marker (HRV) in the collective visualization. There are many other biomarkers that are related to stress, such as GSR, EEG, PD [73]. When giving feedback with diverse types of markers, one way is to map all these stress markers to the same scale, for example, time. An other way is to use the stress index [77], which is a single-value computed from several stress-related signal sources.

The current work was only deployed in the lab setting within a limited time span for engaging self-reflection in the collective context. A long-term field study to verify the efficacy of reflection in a long-term application can be explored in future work. Nonetheless, when the infrastructure enables continuous tracking, the users may require a continuous traceable history. In this case, using different shapes or spirals of different colors [7] may be combined with users' stress along with time, to enable a clear interpretation of current and history status supporting further reflection.

The challenge for scaling the visualization to a larger group is the increasing amount of information to display. Using an interactive visualization could be a plausible solution to provide only the information of interest to the user. For example, a user can touch the AffectiveWall display to scale the timeline, browse the details, and filter unwanted information. Interaction designers should also consider incorporating seamless interaction techniques such as proxemic interactions [78] to provide tailored information to the target users in a more proactive way.

4) REFLECTION STAGE

Short-term reflection is valuable in bringing awareness of current status, and *long-term* reflection is valuable in identifying trends and patterns [8]. Our design aims to drive both short-term and long-term reflection in a collective context through providing a time-series data visualization. However, the test duration is not long enough to see users continuously reflecting in a longer period. Barriers in the reflection stage can be described as the difficulties in retrieving, exploring and understanding information [8]. Accordingly, the future design could proactively push data-driven insight, provide easily traceable data, and moreover, build connections between users' daily activities and data-driven insight [44] continuously to engage in sense-making.

In addition, another challenge when socially interpreting personal data is *privacy*. Based on the positive user feedback on the anonymity and obfuscation (avatar) mechanism, it is left for future research to test whether a privacy-preserving display outperforms a non-anonymous display and to gain more insight into the office workers' interactions. Also, participants, who were more stressed in the user study were more reluctant to share their results with others. To preserve privacy based on the willingness of sharing, future research can also investigate and explore under which circumstances they would like to reveal [79] themselves or make efforts to identify others.

5) ACTION STAGE

Our current system has not been moved into the action stage yet, so the barriers between the reflection and action stages still exist. As with fitness tracking PI systems, the doubts regarding whether reflection helps stress management remain before the users really take remedial actions [8]. Therefore, future work can consider using the insights extracted from our study to provide actionable goals [80] that can engage people in taking actions to manage their stress. Providing immediate feedback on their action's progress helps to improve their sense of self-efficacy [10] and to stay engaged in their behavior.

B. DATA DISCLOSURE TO THE MANAGEMENT HIERARCHY

Individual workers may hesitate to contribute their physiological signals, because of the risk of allowing their personal identifying information (PII) [81] to be misused. Nonetheless, as the data is anonymized, the manager can only recognize the uneven distribution of the workload within the group, and the overall stress level of the entire group. In this way, the manager cannot identify the most (un)stressful employees. Instead, the manager reflects and adjusts the level of task loads to increase group productivity, or balance the workload among all the workers within a group. Therefore, the anonymity mechanism protects the visualized data from being misused.

C. IDENTITY DISCLOSURE IN ANONYMITY

Typically, the anonymity mechanism holds its validity because no one in the system wants to disclose his or her identity to anyone who might be the most stressed and hurt one's feelings, and therefore the entire system remains anonymous in a stable state, which is known as the *Nash Equilibrium* [82]. However, the self-anonymity could be infringed if a user voluntarily discloses his or her identity to another, or anyone outside the group discloses the participant's identity (un)intentionally. In the worst case, when most of the users in the group disclose their identity to each other, the remaining one's identity could be automatically disclosed. Although we encourage the participants to share their personal feelings and situations with their colleagues, as sharing is a form of reflection that can increase people's engagement, the participants should maintain the anonymity protocol during their sharing to avoid the involuntary disclosures that harm other's feelings. Such a social protocol that avoids the self-disclosure issues should be set up and well explained to all the participants. Additionally, getting more participants involved in one visualization can also build up a more resilient anonymity mechanism that prevents the auto-disclosure problem, though the increasing scale of the visualization should be deliberately designed.

Another way to avoid the identity disclosure problem is visualizing stress-related information as an obfuscated collective without revealing personal information. However, it is unclear how individuals could engage in changing their behavior without tracing their personal information. Further investigation on providing incentives to engage the individuals in contributing to the community could be continued.

D. HEALTH INFORMATION DISCLOSURE THROUGH HRV

AffectiveWall only visualizes HRV, which is a physiological index that directly relates to physiological stress. It might reveal the cues of other mental disorders that are (in)directly related to HRV, but such a partial cue is often insufficient to conclude its existence (e.g., cardiovascular diseases [83]). Nonetheless, stress has been described as being associated with emotional disorders, such as anxiety [84], [85]. Other people in the group would not distinguish the abnormal HRV from a normal stressed condition, but the person who knows that (s)he has anxiety can identify his or her personal status and seek help.

E. IMPLICATIONS FOR LONGITUDINAL STUDY

In our studies, we chose to apply acute stressors to the participants by asking them to perform collaborative calculation tasks. Although the applied stress is observed to have statistical significance, the nature of such a collaborative calculation task may not be representative enough of all the kinds of stressors that people experience in a naturalistic setting. A longitudinal study may uncover how the daily stressors affect coping with long-term stress. Nonetheless, valid measurements of long-term stress levels should consider the guidelines as follows: 1) Exclude the measurements under other confounding stressors, such as physical exercise, medicine intake, sickness (e.g., migraine), and other acute stressors [86]; 2) Create a reproducible context in how to take the measurement (e.g., PPG sensor), when to take the measurement (e.g., after wakeup, before meals), and the frequency of the measurement (e.g., three times a day); 3) Establish a statistical baseline for individuals to identify their abnormal physiological responses from the previous records. We hope our results can warrant and guide future work towards this direction of the investigation.

VII. CONCLUSION

Stress management was a heated multidisciplinary discussion for decades. However, in the field of HCI, there is a lack of techniques and interventions for facilitating reflection of collective stress. AffectiveWall transfers the individual's vital signals into a stress index shown in a shared context, draws awareness of collective stress, and further motivates the individuals to compare their physiological signals and their subjective stress in both individual and organizational contexts in their reflection. Users can read the visualizations and change their perspectives based on the visualizations; in other words, the insights into physiological signals help the users in understanding their physiological stress and in reflecting on their subjective feelings. The visualization was also tested to be stress-free in reflection, showing that the anonymized visualization itself was not a source of stress. The qualitative results show that AffectiveWall evokes self and social reflection, and improves the communication of sharing. Users consider anonymity an important issue. We also discussed the various medical and social aspects and potential barriers, which is essential before introducing such a system into practice. There still remain important questions to be answered, and both the implementation and the user studies of this article provide a solid basis for addressing these questions. It is a preliminary yet important step towards workplace stress management.

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