Visualization of Time-Series Sensor Data to Inform the Design of Just-In-Time Adaptive Stress Interventions

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ABSTRACT
We investigate needs, challenges, and opportunities in visualizing time-series sensor data on stress to inform the design of just-in-time adaptive interventions (JITAIs). We identify seven key challenges: massive volume and variety of data, complexity in identifying stressors, scalability of space, multifaceted relationship between stress and time, a need for representation at multiple granularities, inter-person variability, and limited understanding of JITAI design requirements due to its novelty. We propose four new visualizations based on one million minutes of sensor data (n=70). We evaluate our visualizations with stress researchers (n=6) to gain first insights into its usability and usefulness in JITAI design. Our results indicate that spatio-temporal visualizations help identify and explain between- and within-person variability in stress patterns and contextual visualizations enable decisions regarding the timing, content, and modality of intervention. Interestingly, a granular representation is considered informative but noise-prone; an abstract representation is the preferred starting point for designing JITAIs.

Author Keywords
Stress; Stress Management; Visualization; Just-in-time Adaptive Interventions (JITAIs).

ACM Classification Keywords
H.5.m. Information interfaces and presentation (e.g., HCI): Miscellaneous.

INTRODUCTION
Prolonged and recurring stress can disrupt daily life and affect productivity through symptoms such as migraine, sleep deprivation, and chronic fatigue [4,36]. Stress is generally defined as the physiological and psychological changes that results from a stressor — a situation in which environmental demands tax the adaptive capacity of an organism [12]. A 2013 study by the American Psychological Association's American Institute of Stress showed that 77% of people regularly experience physiological symptoms of stress (e.g., fatigue, headache) and 73% experience psychological symptoms (e.g., anger, nervousness)[1]. In this report, 48% mentioned sleep deprivation caused by stress and 33% mentioned living with extreme stress, indicating a need for professional help. In a separate study, nearly 50% of US workers reported needing help in learning how to manage stress[2].

Just-In-Time Adaptive Interventions (JITAIs) hold great potential in helping people manage daily stress experiences [35]. A JITAI is an intervention that offers support just-in-time (i.e., when and only when needed) and in a way that accommodates the changing needs of people as they go about daily life (i.e., in their natural environment) [3,24]. A JITAI can be used to (a) remind people to engage in stress-management techniques as they experience stress; (b) help people better identify and address emotionally laden situations as they occur, in their natural environment; and hence (c) support long-term learning of stress-management.

Despite this potential, lack of theoretical and empirical evidence is considered to be the major barrier hindering the development of interventions for supporting stress management (Just-in-Time-Adaptive Stress Interventions, JITASIs). Most current empirical evidence and health behavior models do not provide insights on the dynamics/transience of daily stress experiences, thus providing no guidance on when and how to deliver JITASIs [25,37]. Sensor data collected in the field can be used to close this gap, helping researchers build the empirical knowledge base necessary for developing JITASIs.

Traditionally, researchers have relied on retrospective patient self-reports for assessing stress [8]. This approach is expensive, time-consuming and is also prone to recall bias [13], offering only disconnected snapshots of events perceived as stressful. Recently researchers have started

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[1] http://www.statisticbrain.com/stress-statistics

[2] http://tinyurl.com/p8btqcb

utilizing sensors to collect objective measures of stress [1,21,38,40]. However, the majority of this work has been conducted in lab settings, failing to capture daily experiences of stress as they occur in the natural environment. Another line of research has focused on capturing sensor-based stress data either in specific locations (work or home), or utilizing a subset of digital-life information (e.g., calendar entries, emails, Facebook posts) [1,20,21]. Although this may be more ecologically relevant than laboratory work, it needs to be paired with continuous measures of stress for better contextualization.

Advances in sensing technology have made it feasible to collect objective, continuous, ecologically valid data about individual responses to stressors [34]. Many people, especially technophiles, have embraced a movement toward the "quantified self," in which rich daily-life data are amassed [10,26]. What is missing is a way to represent data in an effective manner that aids intervention design.

We propose four novel visualizations (spatio-temporal, temporal, contextual, and event-centric) and examine their effectiveness with six expert stress researchers. These visualizations can serve as a starting point in understanding how to display large, diverse, and complex data in ways that can assist researchers to design JITASIs. For example, we learned that spatio-temporal visualizations aid in identifying and explaining between- and within-person variability in stress patterns; temporal visualizations help in understanding personal baseline; contextual visualizations enable decisions regarding the need, content and modality of intervention; and contextual, event-based, and temporal visualizations together can inform the timing of intervention delivery.

In summary, our work makes three key contributions. First, we identify seven key challenges associated with representing continuous stress data collected in field. Second, we present four novel stress visualizations based on 979,104 minutes of sensor data collected from 40 participants (28 days, 14.57 hours/day) and 164,052 minutes collected from another 30 participants (seven days, 13.02 hours/day). Third, we evaluate the usability and usefulness of our proposed visualizations with expert researchers in guiding the development of JITASIs.

STRESS MEASUREMENT, ASSESSMENT AND MANAGEMENT

Continuous Stress Measurement in Field

Automated assessment of stress in daily life, using physiological sensors, is rapidly growing [9,17,29]. Several research groups have deployed lightweight, wearable sensors in the field for that purpose [20,29]. Kusserow et al. proposed an activity-aware stress model (from accelerometer, heart-rate monitor, and belt computer) that detects the duration and intensity of the stress in the field [17]. Plarre et al. proposed a continuous measure of stress (from ECG and respiration data) that is well-correlated with stress self-reports [29]. We use an improved version of this stress measure reported in [11].

Stress Management

Clinical Practices in Stress Management

Stress-management methods used by psychotherapists include cognitive therapy, biofeedback, therapeutic breathing, and many more [8]. Retrospective self-reports are typically relied upon for assessment of both needs and outcome, and have considerable drawbacks [13].

Sensor-based Stress Management in Lab Settings

Sensor-collected physiological data have been used to provide biofeedback on stress states during lab tasks (e.g., simulated driving [19], cognitive challenges [19,27,28]). MacLean et. al. provided continuous stress feedback during driving using a wearable butterfly [19]. Paredes and Chan investigated the efficacy of four interventions – deep breathing, acupressure, game playing, and social network interruptions [28]. Most notably, these researchers reported that stress interventions can become stressors themselves [19,28]. Interpreting these findings is limited by the artificiality of the environment and the stressors.

Sensor-based in-Field Stress Assessment and Management

An emerging thread of research focuses on use of sensors for management of stress in the field [1,20,21,30]. One such system, AffectAura, logs user activity and physiological state using audio, visual, and sensors and aims to support reflection [21], but was developed for use only in office environments. In similar lines of research, Mark et al. investigated stress in relation to multi-tasking and computer use [20], while Bakker et al. examined stress at work utilizing sensors and calendar information [1]. We extend this research by assessing stress in the context of daily-life settings. We put particular emphasis on the visualization of the data to support designing JITAIs, a need that has not been satisfactorily addressed in prior work.

STRESS DATA COLLECTION AND INFERENCE

We conducted two mobile health studies to investigate the relationship between stress, user behavior, and context (e.g., conversations, activity, and location). Study 1 was conducted on 40 illicit drug users; Study 2 was conducted on 30 university students. We chose these two very different populations to enhance diversity, examine a broad range of stressors, and to learn about population-specific pattern of stress. These two study groups are very different when we think about stress; they differ in frequency, sources, and patterns of stress. For instance, among others, students experience seasonal stress due to assignment deadlines and exams while the drug users usually have stressors related to finance due to low socioeconomic status and job instability. Both studies were approved by Institutional Review Boards (IRBs).

Devices and Sensor Measurements

During the study, participants wore an AutoSense sensor suite underneath their clothes. AutoSense is an unobtrusive, flexible band worn around the chest [7], with a two-lead electrocardiograph (ECG), 3-axis accelerometer, temperature sensors (ambient and skin), a galvanic skin response (GSR) sensor, and an inductive plethysmography sensor for respiration (RIP). The sampling rates were 128 Hz for ECG, 21.3 Hz for RIP, 16 Hz for each accelerometer axis and GSR, and 1 Hz for the temperature sensors and battery level. Samples were sent to a smartphone using ANT radio[3] at 28 packets/second, where each packet was 8 bytes and contained 5 samples. The smartphone stored data from its built-in GPS and accelerometers. Participants used the phone to complete system-initiated self-reports (EMAs) and report drinking, smoking, or drug-use episodes.

Study Procedure
We trained the participants to use the devices and to attach and remove the sensors, and asked them to wear/carry all the devices during their waking hours (except during showers and contact sports). We asked them to complete questionnaires when prompted and to record smoking and drinking events. In addition, we asked them to visit the lab daily for data uploads. They completed an Equipment and Experience Questionnaire at the end of the study.

Study 1: Illicit Drug Users
We recruited polydrug users from an ongoing study who agreed to wear AutoSense. We conducted this study for four weeks to maximize the likelihood of capturing instances of drug use. We asked participants to record whenever they smoked a cigarette, used any psychoactive substance (e.g., cocaine, marijuana, or alcohol) outside of a medical context, or felt overwhelmed, anxious, or stressed more than usual. Urine was tested three times/week to verify drug self-reports. Participants were compensated (up to $380) for adhering to the study protocol.

Study 2: University Students
We recruited 30 students from a mid-size US university. The study lasted one week per participant, covering all days of a week. Students were asked to complete system-initiated self-reports on the phone. They were compensated up to $250. Compensation for both studies was similar to those used in sensor-based behavioral-science studies [23].

Inference of Stress, Semantic Location, and Context
We used the stress-inference model proposed by Hovsepian et. al. as it has been validated on independent data sets in lab and field settings [11]. This model infers whether a one-minute measurement corresponds to a physiological response to a stressor using inter-beat interval, heart-rate variability (HRV), respiratory sinus arrhythmia (RSA), and IE ratio, among other measures. It was trained using physiological data collected from a lab study (n=21) and tested on an independent data set in the lab (n=26) and in the field (n=20). In cross-subject validation, the model classified stress and non-stress minutes in lab with 89% recall with 5% false positive rate. It obtained an accuracy of 72% in predicting each of the 1,060 instantaneous self-reports of stress provided by 20 independent participants in the field environment. More details on this stress model is reported in [11].

Semantic labels of locations were obtained from GPS data collected on the study phone. A subset of the labels (home and office) was provided by participants during the post-field study interview. Labels for other locations, such as stores, were generated with the Semantic Context Labeler proposed in [14] (see [33] for details). We utilized participants' self-reported data to get access to activities and their contexts along with responses to EMAs.

CHALLENGES IN STRESS VISUALIZATION

Volume and Variety of Relevant Data
Visualizing stress data collected by sensors from the field is still challenging as stress can change rapidly and can be affected by many spatial, temporal, social, physiological, psychological, and environmental factors. The collection of all these different types of data not only poses technical challenges (e.g., requiring continuous input and inference from many sensors), but also raises issues of privacy and user acceptability [15]. In addition, the data are often noisy (e.g., intense physical activity and high stress situations result in similar physiological profiles). Here we focus only on the challenges associated with stress data visualization.

Identifying Stressor(s) is Complex
Stress can result from a single precipitant or from the interplay of multiple precipitants: temporal (upcoming exams), spatial (driving in a difficult intersection, living in an unsafe neighborhood), social (meeting with a difficult supervisor), behavioral (urge for drug), and other (unanticipated deadline). Any one factor may be insufficient to explain a specific episode of stress. For example, a student may feel stressed in the morning on his way to school due to an approaching exam. The time (morning) and physical state (walking) may not reveal the real stressor. To avoid such incorrect inferences, it is imperative to consider pre- and post-states.

Multifaceted Relationship between Stress and Time Stress visualizations need to scale across time – they need to make sense when based on data collected from a day, a week, a month, a year, or many years. For example, stress researchers may need to access an individual's entire life's data at yearly, weekly, daily, or momentary scales to understand baseline stress for the individual, his reaction to different stressors, and to design just-in-time-interventions. For example, if an individual has elevated stress every Thursday between 11:00am and 12:00pm and during this period, his location is identified as work; an appropriate intervention might be implemented automatically. But, it is extremely difficult to identify such associations when data are collapsed across time or across individuals.

[3] http://www.thisisant.com/

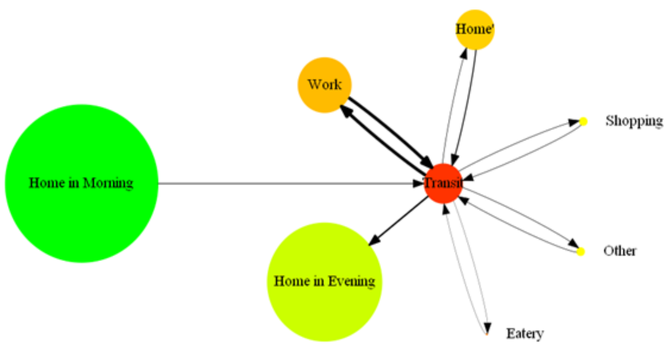

Figure 1. Participant stress profile. Circles and edges represent locations and transitions between them. The size of a circle is proportional to the time spent at a location and the width of the edge is proportional to the number of transitions between nodes. Color represents stress intensity (green = negligible, lime-green = low, yellow = moderate, orange = high, red = extremely high).

The Person-dependent Nature of Stress Makes it Difficult to Create Generalized Stress Models

Different individuals react to different stressors differently, and one individual can react to the same stressor differently in different contexts. For example, driving, a commonly acknowledged stressor, may *relieve* stress for some people, some times. Interaction with a spouse can induce different levels of stress or stress relief, depending on the nature of the relationship. Wide person-level variability makes it difficult to come up with generalized stress representations.

Scalability of Space

Similar issues arise when we consider spatial environments. For example, an individual's resting place can be his home, a relative or friend's home, or a hotel when travelling. With the growth of commuting and out-of-state jobs, the amount of people using multiple places as their "home" is also growing. Similarly, individuals can hold multiple jobs, resulting in multiple workplaces. Capturing the diversity of space without overly complicating the representation is challenging. For example, an individual holding two jobs may experience different stress levels in each job. Using an average stress value across both jobs would be misleading.

Need for Analysis at Different Levels of Granularity

Stress visualizations need to make sense at a glance, but also need to enable fine-grained examination. Fine-grained visualizations are challenging due to the large range of possibilities associated with physical, social, and behavioral states. Collapsing those possibilities into generalized categories for pattern identification is also extremely challenging. Individuals may engage in multiple activities at the same time (e.g., eating and listening to music while working on the computer), and they can be with a variety of people (e.g., friends, family, co-workers, or strangers at public locations), each of whom may contribute to stress differently. A useful visualization of stress needs to show the details without being overwhelming [5].

Lack of Understanding about Needs Related to the Design of Just-in-time Adaptive Stress Intervention

Stress has been widely studied in health research [4,18,22,36]. Technology researchers have also started investigating stress and how to design better technology for stress management [1,13,20,21]. But design of JITASIs is still in its early years, and there has been little systematic study of the best ways to do it. As it is now feasible to collect and measure stress continuously in field, visualizations that enable the design of JITAIs seem the natural next research direction.

DESIGN TECHNIQUES FOR STRESS VISUALIZATION

We propose and examine four techniques for visualizing stress data to assist designing JITASIs. These visualizations were created based on data from studies 1 and 2 and chosen carefully to aid in interpretation, pattern identification, and deciding whether, when, and how to deliver JITASIs. We followed a participatory design approach: we designed a set of preliminary visualizations based on discussions with a group of biomedical researchers (not the expert users participating in the evaluation study) and iteratively refined the visualizations based on their feedback.

Support an Understanding of Overall Stress Levels by Offering a Personalized Stress Profile

Figure 1 presents a graph-based stress profile for one study participant (P18, study 2), highlighting how stress is associated with different semantic state-spaces (e.g., work, home, roadways) that the participant frequented.

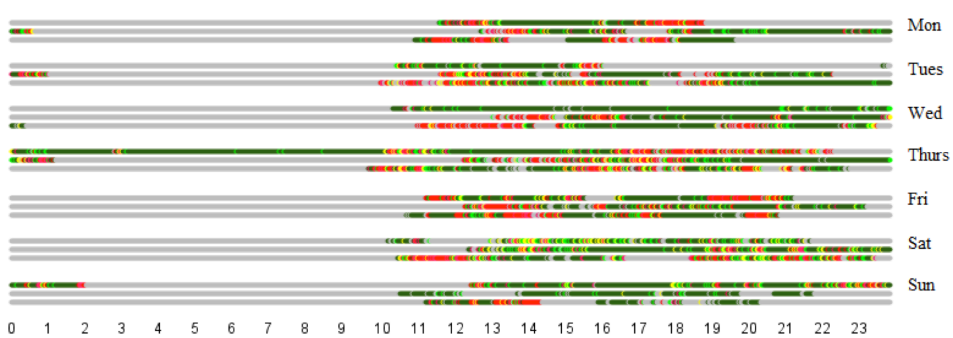

Figure 2(a). Temporal stress profile of participant P4. Each bar represents stress for a day. X-axis and Y-axis represent time-of-day and days-of-the-week respectively. Colors represent stress intensity (red = high stress, green = low stress, yellow = moderate stress, grey = unknown)

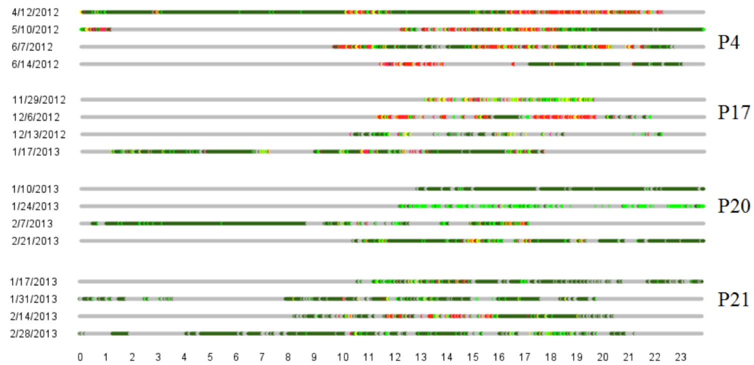

Figure 2(b). Temporal stress profiles of four participants. Colors represent stress intensity (red = high stress, green = low stress, yellow = moderate stress, grey = unknown). Each bar represents a day's stress data, which are grouped by participants.

This visualization provides an at-a-glance understanding of one person's average stress in various contexts, an important first step toward JITASIs [2,32].

To address the challenge associated with scalability of space, we created nodes that reflect the functions of various spaces. For example, each of the three nodes associated with home represents a place where a person lives, yet they are distinguished based on functionality provided at that time (home in morning, home in evening, and home' are defined as places from where an individual begins his day, returns back after all activities, and returns temporarily, respectively). This distinction enables association of stress intensity with the space and also with the activity being performed in that space. This type of representation scales with time: it can be created from data collected over a day, a week, a month, a year, or a lifetime. It can also be extended to visualize data collected via life-logging or activity tracking systems [6]. By providing a summary of the average stress experienced by an individual, it aids quick identification of areas that need attention.

Support Pattern-identification Across and Over Time

Figure 2(a and b) shows participants' *temporal* stress profiles; each bar represents a single day, and color represents stress intensity. Figure 2(a) presents P4's stress data for 21 days (3 for each day of the week), enabling comparison of stress based on time (morning vs. afternoon) and days-of-the-week (weekday vs. weekend, Monday vs. Wednesday), helping to detect temporal stress patterns.

For P4, it is evident that s/he experiences a lot of high stress episodes and they usually occur between 11am-4pm; stress is usually lower in the evenings (after 7:00pm); many of the high stress episodes last more than 30 minutes, and Thursdays are the most stressful days. We also understand that P4 usually ends his/her day around 12am (with few exceptions) and late-night episodes are generally associated with higher stress intensity. Similar representations can be created to visualize other parameters, such as physical activity. Figure 2(b) presents data from 3 different Thursdays for four different individuals (P4, P17, P20, and P21). Multiple Thursday data from each participant enables within-person comparison (for P4, more stressful episodes occur between 11am-5pm), while data from different

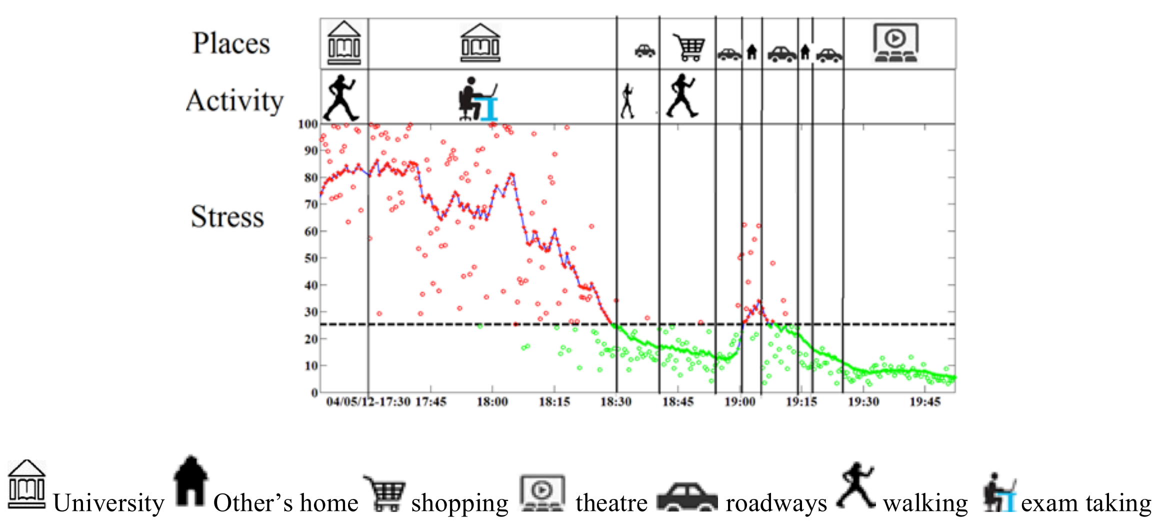

Figure 3. Contextual stress profile of a participant. X-axis shows time, Y-axis shows stress level and context (activity and location). Black dashed line represents baseline stress.

participants support between-person comparison (P4's Thursdays are stressful while P20's are more relaxed). Such representation can aid to answer queries such as what are the most stressful times on Thursdays, how are the stressful episodes distributed, is there a recurring pattern of high stress episodes – aiding identification of temporal patterns to uncover what makes Thursdays the most stressful day of the week. Other temporal (e.g., early morning, late afternoon) and contextual factors (e.g., office, home) can also be used to create similar representations.

Support Investigation of Data at Finer Granularity

Stress prevention requires knowledge of complex combinations of precipitants. Figure 3 (participant P31, study 2) shows one possible representation technique: stress is displayed as a function of location, activity, and time. Areas are segmented and annotated based on activity and location. High-stress segments correspond to exam and driving while low-stress segments correspond to socializing, entertainment, and walking. Such visualizations can provide important detail about stress intensity, potential stressors, and the associated context, aiding researchers to decide if an intervention is needed and how to design it.

Relationships between Stress and Events of Interest

Stress researchers and psychotherapists may prefer to use event-specific stress profiles like the one shown in Figure 4, which represents smoking events and stress associated with these events. Researchers may want to deliver an intervention only when stress is associated with the risk of an adverse event (e.g., a lapse to smoking) and an event-based stress profile may help researchers understand what contexts elevate that risk. In Figure 4 (participant P4, study 1) the first few days contain fewer smoking episodes and are associated with lower stress intensity. Many of the smoking events occur at unknown locations (not home or work) late in the afternoon or evening. On most days the number of smoking events was less than 3, but on a few days it is more than 6. Intervals between consecutive smokes were shorter on those days. Automated capture and representation of continuous sensory data thus enables investigation of individual's stress level and stressors in a much finer granularity, and shows promise for better intervention design.

Utilize Interactivity to Access All or Parts of Dataset

To design JITASIs, researchers need to understand overall stress patterns, influences of different stressors, and any rare but intense stress episodes. The proposed visualizations meet these needs by allowing exploration of details on demand. For example, Figure 2(a) presents stress data for all the days of the week. Each day is represented using a single bar, and three bars representing the same weekday are positioned together to facilitate pattern-finding. Similar representations can be created based on year-long data where, for example, all the Mondays are represented with a single bar and then expanded to show each Monday. In real-life deployment, users will interact with the data using filtering mechanisms (e.g., show only the Mondays that contain 5 highly stressful events lasting for 10 minutes or longer).

EVALUATION STUDY

We conducted an exploratory study [39] to evaluate our visualizations in terms of two major areas of design: Usefulness and Usability (for development of the JITASIs). This study was approved by the IRB of our institution.

Participants

Eight experts in adaptive intervention design were emailed about the project, and six agreed to participate. They were biomedical researchers (four men, two women) at four different universities and were interested in behavioral and preventive medicine and the design and evaluation of health interventions. Three were stress researchers and the other three specialized in interventions for behavioral health problems. Their post-doctoral experience ranged from 6 to 26 years (mean: 13.2). No participants were color-blind (self-reported). The study lasted between 60~90 minutes. Participants did not receive compensation.

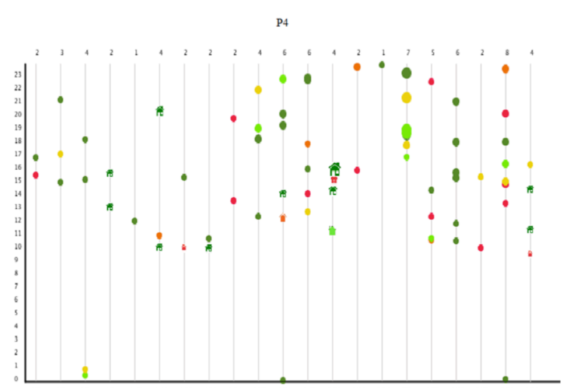

Figure 4. Event-based stress profile of a participant. X-axis shows days and y-axis shows time-of-the-day. Size represents number of smoking episodes and color represents associated stress level. Icons are used to represent location (= home, = work, = other location than home and work).

Method

Each study session was divided in two phases. In the first phase, each participant was briefed about the visualizations. In the second phase, participants were asked about the usefulness and appropriateness of the visualizations in aiding the design of JITASIs, and about their overall opinions of and degrees of interest in the visualizations (see Table 1). Participants had access to a set of visualizations based on Figure 1-4. These visualizations were created using data from 16 participants (10 from Study 1, 6 from Study 2) randomly selected from our total 70 participants. All experts were shown the same visualizations, and were asked to consider all the visualizations together and provide specific examples of how a visualization could be used to inform the design of JITASIs. As our goal was not to compare the visualizations, but to learn whether and how they could inform JITASI design, we didn't ask questions regarding any specific visualization in supporting JITASI design. The sessions were audio recorded. We also collected data about how much time was spent understanding any specific visualization technique, and how many times participants refered to a particular visualization in relation to the design of specific attributes of JITASI (timing, modality, content).

Person-Centric
Do you think the proposed visualizations are useful for understanding the stress level of a person?
In which ways the proposed stress visualizations assist you in designing person-centric interventions? Please give an example of how the proposed visualizations could help in making the interventions person-centric.
Timing of Intervention Delivery
Do the stress visualizations assist you in deciding when to deliver an intervention? If yes, please give an example of how you could use this visualization to decide the timing of the intervention.
Content of the Intervention
Do any of the proposed visualizations assist you in deciding how to adapt the content of the intervention? If yes, in which ways the proposed visualization(s) can help you to adapt the content of the intervention?
Modality of Intervention
Do the different stress visualizations assist you in deciding how to adapt the modality of the intervention?
Frequency of Intervention
Do the different stress visualizations assist you in deciding how to adapt the frequency of the intervention?
Overall Opinion
What would be your biggest concern about using such visualizations to design JITAI? What would be some ways to improve the proposed visualizations?

Table 1. Sample questions asked during interview.

RESULTS

Abstraction Highlights Factors Contributing to Stress

Abstraction was imperative for understanding of overall stress states of an individual and to identify areas that need help. While our participants wanted to know about the specifics of stress (e.g. what caused it, where it occurred), they first wanted to know about the person's overall stress profile. They only expressed interest in learning about stress in specific contexts after understanding a person's general stress trend. Five out of six participants stated that the abstract (summarized) representation of stress (Figure 1) is a good starting point for JITAI design as it highlights the major areas that deserve attention. To quote E6:

"Figure 1 is my favorite as it gets rid of all the noise present in the data and offers a clear picture about where to focus your attention. For example, I can understand that transit is a major stressor for this individual and start to think about the types of interventions that can be offered. After identifying the main stressor, I would use figures 2 and 3 to decide the timing and modality of the intervention. I would always start from figure 1 which shows me the average stress level across many days." – E6

Participants also said that as intervention designers they would need to access all types of representations, but for general users they would recommend abstract (Figure 1) and contextual representations (Figure 3).

Granular Profiles Aid in Understanding Personal Baseline

Our participants preferred the granular stress representations (Figure 2) to identify not only patterns of stress, but also to learn about an individual's experience with stress during daily life. Intervention design requires knowledge about whether a stressful event is a recurring one that needs attention or a one-time-incident that is still important, but does not require the same level of attention. It also requires an appreciation of individual differences. Temporal stress profile can assist researchers in understanding personalized stress baseline. To quote E3:

"We all have different thresholds for stress, being on a roller coaster may be fun for somebody but this is stressful for me. Some people can be very stressed most of the times of the day, when others may not. Figure 2 (a and b) gives me very good ideas about baseline and individual difference. Again, understanding the baseline would give me a very good perspective on event-based stress" – E3

Participants E1 and E6 noted that the more granular representations in Figures 2(a) and 2(b) are highly informative, but may become overwhelming even for expert researchers (E1) and can be prone to noise (E6).

Spatio-temporal and Contextual Stress Profiles Assist in the Design of Personalized Interventions

People experience and react to stress differently, so interventions probably require some personalization. Our participants commented that Figures 1 and 3 looked particularly useful for that purpose. Figure 1 shows stress intensity related to specific locations or activities, collapsed over time; Figure 3 shows a timeline of stress intensity, with locations and activities labeled. E3 stated:

"Figure 1 helps to design an individualized treatment plan. It goes beyond temporal pattern of stress and very quickly enables you to nail down whether to intervene or not. Figure 3 on the other hand helps me to think about what should be the intensity of the delivered intervention. I can calibrate the intensity of the delivered intervention based on the persons stress level" – E3

Because each delivery of an intervention interrupts the participant's activities, and not all interventions are meant to be repeated frequency, interventions should be limited. The contextual representation of stress can help researchers to select stress episodes where a delivered intervention would have highest impact:

"Figure 3 is very impressive; I really like it as on the surface it shows that there is a high co-relation between location and stress without even thinking about the details about what this data actually means." – E3

Temporal Profiles Aid in Selection of Intervention Frequency

Temporal stress representations (Figure 2) not only highlight times associated with high stress (or less stress); they also indicate what the frequency of interventions for a person on a given day should be. If people who experience few high-stress episodes suddenly start experiencing more, they may require help in managing stress at each episode. On the other hand, people who have many moderate- to high-stress episodes throughout the day may be annoyed by an intervention at every episode.

Temporal Details Coupled with Contextual Profiles can Aid in Selecting Timing, Content, and Modality of Intervention

Temporal details help researchers identify an individual's stress patterns over time. Contextual stress profiles show the individual's stress responses to different events and places. Together these representations can inform the need for and timing of intervention. In addition, access to contextual information can facilitate the selection of contextually appropriate intervention timing, content and modality. For example, if an individual experiences high stress and is walking or on public transportation, s/he can be advised to listen to a mindfulness-based intervention. However, if the individual is driving or attending a meeting, perhaps no intervention should be delivered to avoid distraction during driving or social harm at the meeting, irrespective of the stress intensity. To quote E6:

"I need the contextual intervention to decide whether I need to provide an intervention or not. If the individual experiences high stress during driving, I could use Figure 2 to understand whether it is a common pattern or not. I could use Figure 3 to determine when exactly to deliver the intervention. It also provides ideas about what would be an appropriate modality to use for delivering the intervention."- E6

Identifying Patterns of Stress is Feasible, even with Condensed, Granular data sets

Our participants were able to identify stress patterns comfortably even when the data were very granular. Every participant was able to identify multiple stress patterns from different visualizations. Driving was identified as the most common stressor, and the most common temporal pattern was that individuals were more stressed between 12pm-6pm and least stressed between 10am-12pm. Some participants even narrowed the high-stress time between 3pm-6pm and commented that people may experience a large *number* of high-stress episodes between these hours on weekdays, probably due to meetings or deadlines. Our participants even tried to combine data represented in different visualizations (Figure 2 and 4) and tried to speculate what might be contributing to smoking episodes (Figure 4) and whether there is a causal relationship between high stress and smoking at different times or locations. After identifying any specific stress patterns, all of our participants wanted to dig deeper to learn the causes of stress. Every participant expressed a desire to start from either the spatio-temporal or temporal stress profile, and then use the contextualized profile to examine details. This indicates that no one type of stress visualization is sufficient; rather, they complement each other and need to be presented together to inform the design of JITASIs.

Usability of the Visualizations

Table 2 summarizes the pros and cons of the individual visualizations, as expressed by our participants. All participants preferred the spatio-temporal profile to identify problem areas and to personalize content. Four of six participants considered the contextual stress profile highly effective in informing the content and timing of intervention, while the temporal visualization was preferred for understanding how individual baselines should determine intervention timing. Participants said that the visualizations were easy to understand and felt confident about using them. Considering the fact that the participants had never seen the visualizations before, it is encouraging that they were able to engage with them quickly.

Overall Opinion and Interest in Future Use

All the expert participants considered the visualizations useful and said that such visualizations could make individuals more stress aware. All of them expressed an interest in using these visualizations to design JITAIs. Four out of six expressed an interest in using such visualizations for their own stress management. One of the two who did not (but found them useful for designing JITAIs) mentioned "*experience with past stress management tools*" as the rationale. E1 said that Figures 1 and 3 will be equally effective for intervention designers and non-expert users aiming to become more stress aware, but that the details in Figure 2 may overwhelm non-expert users. Our findings indicate that further research is warranted to investigate what types of stress visualizations will be applicable to users with different expertise and need.

DISCUSSION AND IMPLICATIONS

Identifying Stressors is Challenging even in the Presence of Contextual Cues

Integrating contextual cues in the stress representation provides better access to the underlying causes of stress. However, even with these cues, it is difficult to ascertain "what causes stress." Our participants had access to contextual information such as time, location, and activity and still found it difficult to pin point specific stressors. For example, participants wondered whether the stress seen at work was due to the nature of the work or from interactions with coworkers. Similarly, the average stress level associated with being at home in the evening may result from a bad, hectic day at work, or from rough traffic. Inclusion of technology such as Google Glass may provide access to more context, and aid in identifying the stressors. However, even when context is well characterized, it can be challenging to identify specific causes of stress. A study that delivers interventions in the presence of different stressors in real time may provide better understanding about causation. But, such studies may fail to pinpoint specific stressors due to the presence of residual stress resulting from unrelated activities.

Visualization	Pros	Cons
Spatio-temporal	Highlights personalized stress intensity in relation to location and time-spent, removes noise by aggregation	Timing and frequency of information can't be captured
Temporal	Helps to understand personal stress baseline, pattern of stress, and highlights frequency, duration, and intensity of stress	Complexity can increase with increased data volume, requires careful investigation
Contextual	Highlights occurrence and intensity of stress as it occurs in field, helps in determining timing and content of an intervention	Prone to noise, doesn't scale well with large amounts of data, can introduce privacy-risks
Event-Centric	Combines sensor and user-reported data, Enables study of stressors linked to an event-of-interest	Does not scale well with time and space

Table 2. Pros and cons of the proposed visualizations.

Personalized, Contextual Representation of Stress is Necessary but not Sufficient to Determine the Need for an Intervention

Real-time biosensor information is not sufficient to decide whether to trigger an intervention. Different people have different stress receptivity, and the same individual may react to the same level of stress differently at different times depending on what is going on in his/her life, pointing out a need for personalization and adaptation. In addition, many stressful situations (e.g., an upcoming deadline) may not need an intervention. While contextualized stress representations aid in selecting an appropriate intervention, more information indicating the individual's receptivity to intervention at the moment and probability of engaging in an adverse health behavior (e.g., lapse in abstinent smokers) may be needed to decide whether to trigger an intervention. In addition, research suggests that in many situations an individual may be unavailable cognitively, socially, or physically to attend to an intervention [33], pointing to the need to determine an individual's availability before delivering an intervention.

Identifying Recurring, Momentary Stressors Can Assist in the Design of an Appropriate Intervention

Stress episodes can be brief yet intense, and recurrence of such episodes can affect well-being — but research suggests that people are not very good at recalling them [21]. Visualizations based on sensory data are well suited to assist in detecting such episodes and their impact. This information is needed to design the most appropriate intervention. For example, if researchers can identify a pattern of high-stress episodes on Tuesdays at 4:00pm at work when the individual interacts with a colleague, they can suggest ways to modulate these interactions to reduce stress. We aim to uncover visualization techniques that can further our understanding of the person-specific nature of stress and individual reactions to different stressors.

Selection of Participants for the Evaluation Study

Instead of allowing data producers to review and evaluate their own data, we chose to have stress experts evaluate the visualizations. While evaluating the visualizations with the data contributors seems natural, we chose expert evaluators for the following reasons. First, showing visualizations of the data to the data contributors could influence and potentially change their behaviors without any careful consideration of health risks. To mitigate unexpected health risks to the data contributors, visualizations that aim to influence behavior should be designed with the significant involvement of experts. Second, until recently, stress experts rarely had access to continuous stress data and hence may not yet be able to design stress interventions for end users. Therefore, our first step was to enable the experts to explore the dataset without the responsibility of making recommendations to the end users. Third, the development of effective visualizations not only requires time and effort, but also requires access to real data. Hence, the stress visualizations were developed after the data collection studies were completed. In addition, intervention designers may have different goals than end users (data contributors), and thus may have different needs from the visualizations (although we suspect there is some overlap). Hence, the visualizations proposed in this paper may not be the final visualizations that should be presented to end users.

Privacy Concerns Influence Quality of Visualizations

Privacy concerns associated with different types of data have a profound influence on the amount and nature of available data. A considerable amount of sensor data is lost due to shutoff or detachment of equipment at moments when users want privacy [31]. But if such data stay only on the user's device and are used only for self-monitoring, privacy risks are reduced. Increasing user awareness regarding possible risks and benefits thus may increase the possibility of collecting privacy sensitive data. Privacy issues do arise when data are shared with others (e.g., a therapist). Ensuring secure sharing and protecting privacy of sensitive data along with anonymization, transparency and user-driven data control are active areas of research.

For Stress Visualizations, One Size Doesn't Fit All

Stress is highly person- and context-dependent and our proposed visualizations were chosen to capture and reflect this variability. An overview of an individual's stress for a day, week, month, year, or many years would be extremely useful to uncover his or her "universal stressors", however, would not uncover rare but intense stressful events, as contextual and event-centric visualizations could highlight (see Table 3). Our findings revealed that a single visualization type is insufficient to capture and represent all the nuances of stress even for a single individual. Our study is a first step in understanding what types of visualizations aid researchers to design JITASIs. Further research is warranted to identify the best visualizations to support long term personalized stress management.

Task	Preferred Visualization(s)
Sense-making of overall Stress	Spatio-temporal and Temporal
Understanding Personal Stress Baseline	Temporal
Identifying Stressors	Contextual
Pattern Finding	Temporal and Event-based
Timing of JITASI	Temporal and Contextual
Content of JITASI	Contextual

Table 3. Summary of participant visualization preferences for JITASI design.

CONCLUSION, LIMITATIONS AND FUTURE DIRECTIONS

We investigated how to visualize daily-life stress to inform the design of JITASIs for stress management. We identified seven key challenges in visualizing stress data and proposed four types of visualizations based on 1,143,156 minutes of data collected in field. Our visualizations addressed the key challenges posed by massive amounts of sensory data collected from field, and were guided by prior findings in stress management and intervention design research.

One limitation of our study is that we only captured a subset of the contextual data that could have been captured with our sensors, partly due to privacy concerns. Audio and video data could inform us about the impact of social situations, and may become more feasible with growing acceptance of technologies such as Google Glass. We also did not collect digital-life information (e.g., email) [20,21], which might make the visualizations even richer. In the proposed visualizations, we used color to reflect the different levels of stress intensity, which may be difficult to interpret for people with red-green color blindness. We plan to use additional features (e.g., symbols, avatars) to make the visualizations more inclusive.

In this research, we investigated what types of visualizations can aid JITASI design, which is the first step towards realizing the vision of mHealth and Precision Medicine [16]. To support our goal, we evaluated the usability and usefulness of these visualizations with expert stress researchers. However, we believe utilizing these visualizations in a real setting as interventions would lead to better insights. As the next step, we are designing two follow-up studies in which we use these visualizations as interventions. In study 1, 50 romantically involved couples will explore the visualizations together with the researchers to understand and identify ways they can better manage stress. In study 2, 75 daily smokers will receive JITASIs to aid a quit attempt. We believe findings from our current and future studies will yield valuable insights into design considerations for the visualization of stress data and future real-time, stress intervention techniques.

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