Challenges and Opportunities in Utilizing IoT-Based Stress Maps as a Community Mood Detector

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***Abstract*—Stress has been known to cause physical and mental issues like depression, anxiety, insomnia, lower immunity, stroke, as well as leading to suicidal thoughts or violence towards others. Stress is not just a state of mind, but it is measurable. With the ubiquity of Internet of Things (IoT), and the integration with highly sensitive biosensors, it may be feasible to use these devices for detecting stress in public places. Moreover, correlating such stress data with social media streams can lead to insights into the psychological well-being of the community as a whole. We present a framework of such a community stress map based on social media and explore techniques for gathering data for measuring stress levels as well as detecting abnormal levels. This stress map can then be leveraged by emergency and crisis response teams for public safety and help them be proactive in allocating resources to the stressed areas indicated in the map.**

***Index Terms*—Public safety, IoT, social media, stress**

I. Introduction

Preventing societal threats and attaining sustainable public safety are major challenges faced by modern societies. Improving public safety entails making communities more resilient to disasters, terrorist attacks and campus/school shootings which can have devastating effects such as loss of lives and billions of dollars in rebuilding infrastructure and communities. A common implicit pattern leading up to these extreme events or following after them is stress. A recent study reveals that nearly half of the American population is plagued by stress [1], with finances and work problems listed as top contributors to people's stress. In a national survey conducted in 2016, younger adults on average reported higher levels of stress than older people, for example, millennials typically reported 39.5% higher stress levels than baby boomers, showing a 25% steep increase from 2014 to 2015 [2].

Stress is also a known contributor to many other physical and psychological problems, including stroke, headache, insomnia, digestive difficulties, cold and flu, burnout, depression, and anxiety. For example, *stress has been found to be the major cause for suicidal thoughts and actions* [3]. Studies reveal that 60% of mass shooters in the U.S. showed signs of delusions, depressions, and acute paranoia [4], all of which, particularly depression, may be traced to high stress.

Researchers have found *direct ties between stress and aggression*. Experimental psychologists reveal that stress and aggression can create a vicious cycle, that is, sudden stressors often precipitate violent behavior, and aggressive behavior induces an adrenocortical stress response [5]. In organizations and societies, stress also leads to counterproductive behaviors such as sabotage, workplace violence, absenteeism, tardiness, turnover, and even drug abuse [6]–[8].

Detecting an individual's stress with relatively high precision has been attained by conventional methods using body sensors [9]. However, stress detection and management at community and society levels requires major cross-disciplinary innovations in engineering and social sciences. These innovations are more feasible now than ever before, made possible by the revolution of Internet of Things (IoT). Moreover, tiny, low-cost and highly sensitive wireless-capable devices and biosensors are not only technically available and commonplace but economically viable. Perceiving these sensors as IoT devices and equipping them with Internet capability can open the door for detecting and responding to social phenomena such as stress or panic. Such capability of detecting crowds' mood over space and time can improve community health and public safety.

In this paper, we propose a framework to monitor the *mental health* in terms of stress-level of a community at large in the hopes of preventing violent acts of crime such as mass shootings on campus or public places, and giving an additional tool to public safety officials to effectively intervene. In particular, we first a) discuss the challenges and opportunities involved in designing and developing a campus/community stress map (CSM) using IoT devices, and b) present techniques

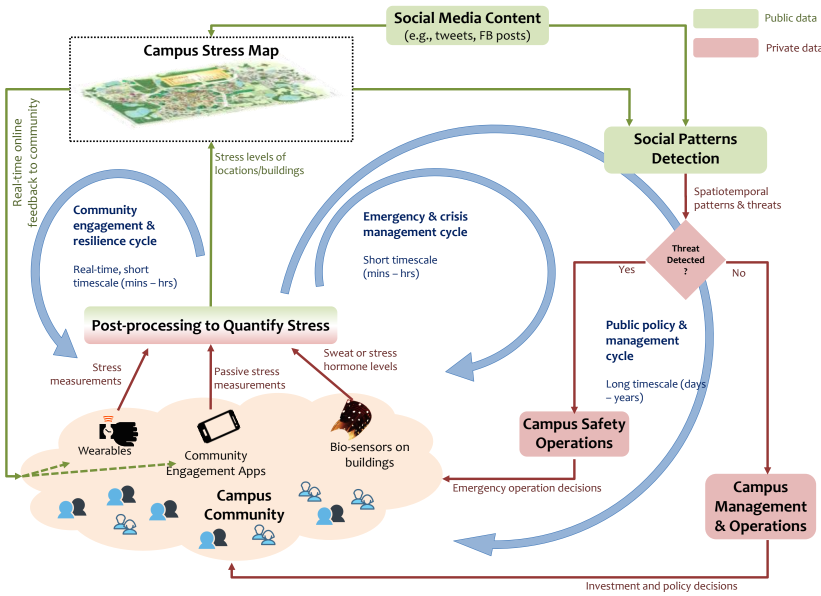

Fig. 1. Community Stress Map (CSM) framework: An IoT-based stress mapping framework for campus community safety.

for utilizing CSMs to improve public safety and well-being. We present emotion maps based on social media data analysis.

II. Community Stress Maps: Approach

The proposed framework of building CSMs is composed of three concurrent cycles and is outlined in Figure 1. Below, we discuss the three cycles, which require a multi-disciplinary effort within the context of a campus community:

A. *Community Engagement and Resilience Cycle*

The main source of information for building the CSM will be IoT devices, smart phones and other wearables of the campus community. The CSM could be made available to campus community and could incentivize downloading of our app (detailed in section III-B) to their smart devices as they will be able to discern which buildings are more stressed in real-time. Such real-time engagement can make the campus community more resilient and agile to various potential threats. Although our primary goal is to measure stress, the framework could be used to measure other psychological aspects, such as anxiety and happiness that may be exhibited by the participants.

B. *Emergency and Crisis Management Cycle*

As in every U.S. state and its many cities, university campuses are equipped with an Emergency Operations Center (EOC), a centralized facility with officials that facilitate response to campus incidents such as hurricanes and campus shootings. Through a web of camera networks on campus, an EOC is able to gain situation awareness. However, it is typically hard to ingest and analyze all the live video feeds leading up to an impending crisis due to the sheer volume of data generated and limited resources to review them. This sentiment was shared by our campus EOC which has 2,000 cameras deployed. The CSM can be used by EOC officials to help identify possible areas of stress build-up as it can survey social media, pick up key words, correlate them to calendar of events and detect unusual patterns using machine learning techniques. This allows EOCs to manage their resources better by sending help where most needed, and hence, minimizing the impact of emergencies on campus. The effectiveness of the CSM will depend on how good it is at differentiating regular activity caused by stressful events such as exams versus irregular activity due to suspicious individuals sighted.

C. *Public Policy and Management Cycle*

On a larger timescale, CSMs will allow campus comunity management to observe various patterns and make investment/reorganization decisions accordingly. For instance, University of Central Florida's management was interested to know how campus people felt while waiting for hurricane Irma to reach Central Florida so that they could improve their hurricane preparedness for future. Likewise, understanding how various parts of the campus "feel" during major events (e.g., political campaign rallies, final examination's week, and football games) can enable better management and policy decisions using CSMs. CSMs may offer a great way to involve IoT devices in public policy and safety decision-making.

III. Challenges: Stress Detection

Detecting stress of people or places is a key challenge for CSMs. We anticipate using multiple stress detection mechanisms. Legacy techniques include wearables that monitor vitals of a person or biosensors that monitor stress hormones [10].

Beyond these conventional methods, we consider the use of social media and smartphone apps for stress detection.

A. Social Media Use for Stress Detection

Social media, such as Twitter, Facebook, and Instagram, have a great potential for emotional and stress assessment. For example, a recent study analyzed over 509 million messages collected from Twitter and examined the diurnal circadian patterns of positive and negative effects, to find that negative effect peaked between 2-3am and remained low during 6am-7pm [11].

Analyzing such streamed data involves, as demonstrated in Figure 2, classification of both stress *genre* and *topic* and the assessment of *actions* that may result from stress. This classification can be handled by machine learning algorithms, e.g., Support Vector Machines (SVMs). Genre refers to the general category of social media feeds, e.g., is the feed related to stress at all or does it describe personal experiences? Stress topic is the domain or stressor being described within the social media feeds. The domain may include study, work, interpersonal relationships, and finances. Lastly, action analysis aims to understand what behaviors the user may be engaged in when they are stressed. For example, tweets such as “Anyone want a drink with me now? So stressed out” or “Stressed! Need to sleep tonight” involve actions that need to be further categorized into either negative or positive, with special attention to the negative actions for stress. Sometimes, there may be no actions reported in the feeds, someone may simply post “#stressed”. To classify the genre, topic, and actions, comprehensive n-gram dictionaries could be developed, e.g., “exam”, “final” and “stress” for unigram dictionaries; and “finals week”, “stressed out” and “failed tests” for bigram dictionaries. Once machine learning algorithms have been developed, they could be applied to assess both the stress level of the individual, as well as the community by computing proportion of stress feeds and validating against specific events occurring on campus during that time.

B. Stress-Sourcing: Crowdsourcing Stress

Smartphones as a sensing device have proven to be a very successful way of collecting personal data for the “larger good” of the community as seen in recent apps e.g., FireChat [12], Open Garden [13] and tethering [14]. When a “larger good” exists for the community, device owners become more willing to share, for example sharing personal measurements through their devices to contribute to the bigger picture of a community’s level of stress. We envision this could be done for measuring stress via an app, StressSourcing, to improve public safety by passive sensing through the smartphone’s accelerometer, camera, or microphone. StressSourcing app could enable us to make stress measurements of the user and infer their stress-level through patterns. A recent study [15] showed the potential of measuring a smartphone user’s stress level in a working environment by looking at the smartphone accelerometer data along with user’s self-reported stress levels.

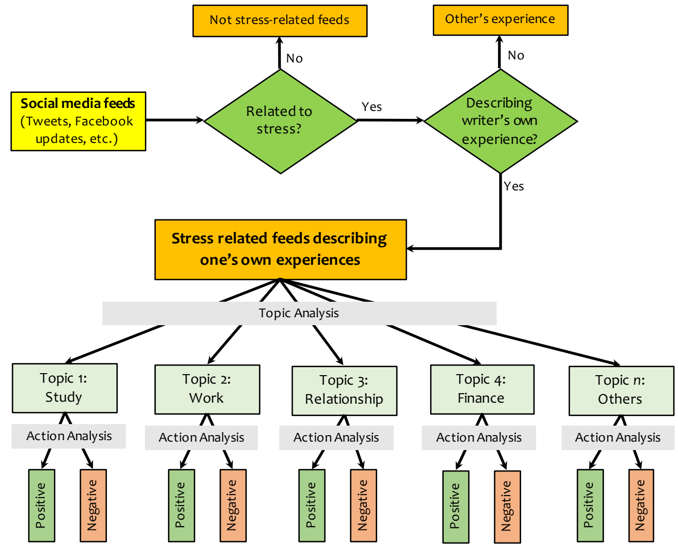

Fig. 2. Support Vector Machine (SVM) machine learning technique used to classify stress feeds by genre and topic, and assess intended actions (positive or negative) embedded in the feeds.

The crucial challenge is to measure stress with minimal use of the data that may be sensitive to user’s privacy.

For a campus setting, the following patterns could be explored: *Walking habits* (e.g., faster walk with respect to others) may indicate higher stress; *shakiness* of movement may indicate leg fidgeting due to stress; *proximity to historically stressed spots* may indicate higher stress (e.g., someone closer to the library is likely to have more stress than a person closer to the cafeteria); and *app use patterns* (e.g., exploring news sites) may hint higher stress while messaging with buddies on social media may indicate a more leisure time with low stress. These types of measurements are technically easy to do in a typical smartphone once the user downloads and allows appropriate privileges to the StressSourcing app.

While the use of StressSourcing app is voluntary, it is still crucial to minimize the overhead on user’s smartphone, specifically data plan utilization due to periodic measurements, data gathering and data transmission by the StressSourcing app. This can be achieved through data aggregation and compression, however, data would need to be transferred to stress monitoring servers in near real-time. One possible strategy is to use unlicensed bands to minimize data plan usage. Device-to-device transfers using a mix of WiFi and Bluetooth interfaces [16] could also be leveraged to avoid relying on the user’s data plan.

C. Accurate Stress Detection from Heterogeneous Sources

For the CSM development, stress measurement data could be collected from multiple sources. Meaningfully integrating these multi-source data to build the CSM without intruding into participants’ privacy is a challenge and requires data science techniques. Multi-level classification and statistical learning techniques could be applied to fuse these multi-sourced data.

There is a need to understand various features measured through each data source. For example, a) StressSourcing app can be used to capture both accelerometer and camera measures; b) wearables can capture heart rate, heart rate variability, and body temperature and its fluctuation; c) biosensors can provide multiple measures on sweat and hormone levels, and d) social media data analysis can result in up to hundreds of linguistic and semantic features such as anger, swearing, and friends. This level of analysis helps understand the predictive validity of each specific measured feature and lays the foundation of higher levels of data integration.

Next, comes data integration that simultaneously takes all the features into account and dynamically assigns weights to the features. We could apply statistical learning techniques for this level of analysis to allow each feature to contribute to the overall score within a data source. For example, the overall stress measure from the social media source may be largely contributed by the anxiety, anger, and sadness features, and less by the food and friends features.

At the third and final level, data integration focuses on the inter-source measures of stress. Similar to the second level, this final level could also use statistical learning techniques but subsumes the four overall stress measures developed at the second level by considering the different predictive validity of each source. This predictive validity may also vary based on the type of stress. For example, for anti-social aggression stress, the predictive validity may be b > c > d > a; yet for exam stress, the rank may be d > c > a > b. For each stress type, there is a need to seek the best weights for each of the four heterogeneous stress sources.

IV. Challenges: Privacy and Policy

A. *IoT-Based Stress Data Privacy*

The ability to collect information negatively correlates with privacy and security, with today's hyper-connected lives creating unprecedented privacy problems. A surveillance system that has a detailed and invasive model of public spaces is unacceptable to the public and the individual. Further, gathering so much information into a single knowledge-base has major security risks, as was observed in the 15 million people's data breach at Experian credit-rating agency [17]. To circumvent privacy and security challenges in the CSM framework, we argue that a value-based approach to data-privacy is needed.

Game theory defines the Value of Information (VoI) as the price an optimal player would offer for a piece of information. In the CSM framework, although it appears that the detection of highly stressed areas of campus would be associated with an arbitrarily high VoI, society already makes such decisions in financial terms, e.g., when determining the budget for the campus police. Thus, it is possible to assign such values *in aggregate*. What is much more difficult is to price a single observation: How much value does a single data chunk c acquired through our IoT system have? One mathematical tool for this is to define the VoI at the margin, as a function of the effectiveness of the responder. How much more efficient will the work of the police be with this information, versus without it? This definition of VoI, called pragmatic VoI has been studied in [18].

We have seen that we can associate a VoI to a chunk of information c. If there is no cost associated with the collection of the information, obviously even an infinitesimally small VoI can lead to the decision that the information must be collected and stored. In practice, the VoI must be weighted against the cost of acquisition, CoA, and the cost of privacy, CoP. The CoA could be defined as the expenses necessary to install and maintain the IoT system. In general, it is characterized by a large, aggregate fixed cost and a much smaller incremental cost per data chunk. The CoP [19] is the reverse of the VoI taken from the point of view of the data owner: How much would the individual pay for the chunk c not to be disclosed? It can be estimated through individual interviews and mobile apps that occasionally allow the user to trade privacy for services provided. Finally, CoP could be estimated in aggregate, studying public policy decisions or damages sustained in privacy breach lawsuits such as those recently filed against Facebook, Apple and others.

Once we have a way to estimate the VoI and CoP of an information chunk c, we can make a decision to keep the information if $VoI(c) > CoP(c)$. In practice, it is difficult to estimate $VoI(c)$ without first collecting c, thus the best we can do is to securely erase c after an initial examination. As more VoI values decay in time, this appears to be a safe choice. However, in many public safety scenarios, the VoI can radically increase when correlated with other information chunks, even if the information chunk is comparatively old. After a cursory examination to estimate the current VoI, we can either discard c securely, or use it in an aggregate C, or retain an anonymized version c'. Anonymization techniques, typically used in citizen science, include adding noise to various parameters such as location or time until de-anonymization becomes impossible [20].

B. *Culture of Preparedness for Campus Safety*

Campus emergency and crisis management is becoming a distinct discipline due to the number of active shooter situations and bomb threats across the nation. The tragedy at Virginia Tech catapulted the importance of emergency programming and notification systems as well as the critical component of assessment and evaluation of these aspects. Although smaller in size than local communities, university campuses are expected to have a higher degree of emergency preparedness because of housing a vulnerable population [21]. Many campus emergency managers have begun utilizing social media to expand communication outreach.

To understand the factors involved in designing policies for IoT integration into public safety operations, the following questions should be explored: (i) How can IoT use, including social media tools, be integrated into campus safety policies and management? (ii) What are the optimal strategies to increase the use of IoT and social media by campus community? (iii) What can both incentivize sharing of the individuals' social media content with campus emergency management and assure that privacy of individuals is not jeopardized? These questions could be addressed through developing and administering a survey to nation-wide campus emergency managers and security directors.

Sustainability of a new technology is heavily dependent on the users seeing direct benefit from it. The long-term viability of integrating IoT technologies, like CSMs, to communities depends on how much benefit they give to these communities. One strategy to measure this is through pre- and post-experiment surveys on campus participants, with the aim to quantify community's heightened awareness of public safety issues and their vigilance against threats.

V. Pilot Study: Stress Maps using Social Media

As mentioned in Section III-A, social media has great potential for stress assessment. In particular, Twitter presents a unique opportunity to analyze language in a real-world setting. In this paper, we analyze tweets' content and linguistic features to uncover the underlying psychological states.

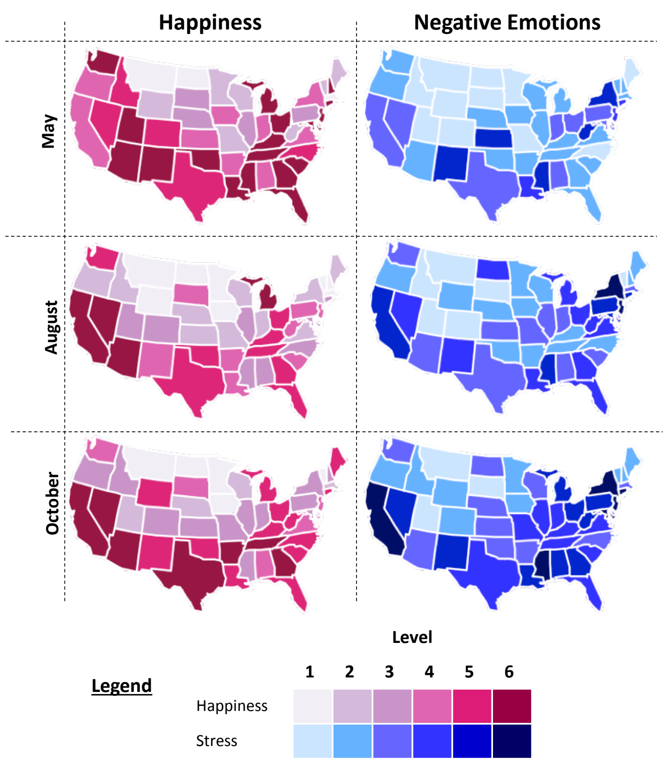

Fig. 3. Emotion heatmaps from our preliminary work on social media data analysis: Happiness and negative emotions (May-Oct 2009).

A. Data Collection and Analysis

To demonstrate the feasibility of creating stress maps by using social media data, we conducted a pilot study and collected over two billion Tweets, posted by 46,908,115 unique Twitter accounts from the Twitter server(s) spanning 18 months from May 2009 to October 2010 through Twitter's Streaming API [22]. This API has a built-in randomization functionality which makes random sampling over all Twitter users. We also limited our focus to tweets in English, originating in the United States. (This data is available upon request.)

In the pilot study, we analyzed the psychological and linguistic features in the Twitter data by using the Pennebaker's Linguistic Inquiry Word Count (LIWC) technique [23], [24], most widely used for text analysis in computational psychology and other social sciences. Analytically, this method computes the word frequency for a particular group or category of word collection, a.k.a. dictionary, that is predefined. More specifically, it computes the number of words in a specific dictionary divided by the total number words in the tweet. For example, in a tweet "Horrible day! I just lost my job today", there are 8 words in total, two of which (i.e., "horrible" and "lost") are part of the negative emotion dictionary. Thus, according to the LIWC method, the negative emotion score for this tweet is $2/8 = .25$. As such, the computation of scores for various psychological and linguistic features depends on specific dictionaries. Fortunately, the LIWC software (available at http://liwc.wpengine.com) includes more than 80 built-in dictionaries, including various categories such as affect, social, cognitive process, perceptual process, and biological process. Each category further breaks down into many subcategories. For example, the affect category includes positive and negative emotions, and the negative emotion subcategory further consists of anxiety, anger, and sadness facets.

Specifically, the positive and negative emotion dictionaries in the LIWC program are respectively comprised of 646 and 751 words or word stems. For example, typical positive emotion words are "happy", "happiness", "happily", "happier", "happiest", "desir*", "engag*", "enjoy*", etc. Similarly, exemplary negative emotion dictionary includes "argu*", "loss*", "pain", "pains", and "painf*". In order to precisely assess stress from social media, we have also specifically developed a *stress dictionary* (available at http://bit.ly/2mbP87b), as a subset of the LIWC negative emotion dictionary, comprising 270 words/word stems, e.g., "abuse*", "attack*", "fear", "insult*", and "terribl*", etc. This stress dictionary has been vigorously tested for its reliability and validity to ensure the psychometric quality in a previous study when the dictionary was first created [25].

B. Results

With the developed stress dictionary, we further analyzed stress and happiness at the state level at monthly intervals. Figure 3 shows the aggregated data per state developed as a time series of positive and negative emotion maps. These maps demonstrate the fluctuations of positive and negative emotions in the tweets over time and across locations (i.e., states). It is worth noting that the granularity of both time and location can be refined for different research purposes. One advantage of creating such temporally continuous emotion maps is to understand the emotion baselines for a given location during a certain time passage, and the historical emotion baselines can be used to evaluate the deviation of the current emotion strength, which may have important implications for public safety for that particular location. For example, if New York's stress level has been stable at 3 (out of 6) during the past year, and suddenly has surged to 6 at the current time point, this spike may indicate the occurrence of serious social events (e.g., public shooting).

Because some of the social media data are associated with precise time and location information, with the same technique, one can derive and analyze stress maps at more granular levels: boroughs of a city, communities in a borough, different areas on a campus, etc. These maps, combined with IoT and machine learning techniques, will be powerful to predict various significant societal events and consequences. Looking at Figure 3, New York seems to have experienced notable increase in stress, which may be linked to several negative public evens including the financial crisis in late 2008, crash landing of a US Airways flight to Hudson River, and car bomb found in Times Square. It is possible that these events may be the cause of the increase in New York's stress. A thorough study of the correlations of such events and the trends in the stress or happiness maps is needed to make more conclusive statements.

VI. Opportunities and Research Directions

More work needs to be done in stress detection. We developed a time series of national maps of happiness and negative emotions, but this is at the state level. More precise maps need to be defined, by refining both location and temporal information, that reflect stress fluctuations in real-time. IoT devices with biosensors capable of vitals-based (e.g., heart rate) or hormone-based stress measurement need to be integrated with CSMs. These devices can be placed on volunteers or public places where individuals' identity can be protected. For example, stress sensors can be placed at door knobs, seats or other locations with high probability of collecting hormonal or vitals data of people. Although it entails certain privacy issues, such measurement of stress/mood of locations or individuals can be crucial in public policy making for emergency response, crisis management and public safety.

Characterizing community-level stress opens several research challenges. In the context of stress-sourcing, there is a need to correlate self-reported stress levels, acquired through apps like StressSourcing with data reported via the user's smartphone's accelerometer. Another question is how to protect user's privacy with minimal data to measure stress by determining not only the quality and types of measurements (camera, accelerometer, etc.), but also deciding what information to retain for processing and analysis. Another worthy research direction during data sourcing is minimizing the data transfer to servers to reduce its impact on user's data plan. Unlicensed bands can be leveraged as well as device-to-device data sharing [16]. More methods need to be explored to aggregate data and transfer it with a high enough frequency to adhere to the real-time nature of collecting and monitoring stress data.

Several worthy research directions arise from the privacy perspective, including defining the value of observation, i.e. the Value of Information (VoI); defining its pragmatic value or effectiveness to a public safety response team, i.e. the cost of privacy (CoP); and data anonymization. In terms of policy, in addition to campus events, out-of-campus events can also have a great impact on campus regulations. For instance, post Hurricane Katrina in 2005, the Department of Homeland Security requires universities to build their own comprehensive emergency management plans (CEMPs) and continuity of operations (COOP) plans compatible with the National Incident Management System [26] and other federal policies and frameworks [21]. The survey study by Zdziarski et al. [27] indicated that 13% of the respondents believe that their campuses are disaster resilient. The study revealed that building strong community partnerships, regular training and exercises, and all-hazards plans are the most crucial factors for disaster resilient campus creation. Given CSMs, more research is needed to formulate the right management policies for handling emergencies such as campus shootings and or other stress-related risks.

VII. Concluding Remarks

In conclusion, we have proposed a framework for detecting stress and developing community stress maps to improve public safety on campus. Inter-disciplinary techniques have been proposed that span computational psychology, pattern and outlier detection algorithms, privacy-preserving wireless and IoT systems, and public safety and disaster management policies and incentives for community participation. We outlined several research challenges and opportunities arising from the design of community stress maps.

Acknowledgments

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