Integrative Sensing Techniques for Building Non-invasive Body Sensor Networks

Chelsea Ko and Sharief Oteafy
School of Computing
DePaul University, Chicago, IL, USA
{ cko2 | soteafy }@depaul.edu

***Abstract*—The span and accuracy of sensors being developed for Body Sensor Networks (BSNs) are rapidly improving, aiding well-being services, and paving the way for real-time *Affective Communication*. While traditionally accurate sensing techniques were either highly invasive or rudimentary in their data, the roadmap of developments ahead shall enable a multitude of dependable analysis of patient monitoring. However, given the spectrum of techniques and tools available, researchers in this domain may find it challenging to balance accuracy, invasiveness, responsiveness and other design parameters of health-centric BSNs. In this paper we analyze and contrast different sensor types and sensing inference techniques, along with the response metrics that they are able to deliver. We further elaborate on their association to responses from the nervous system, and how they correlate to different measures of well-being. To aid future research on AI-assisted patient monitoring, we present current benchmarks for assessing BSN data accuracy, and their cross-validation across physiological signals. The goal of this paper is to assist researchers and practitioners in identifying the best subset of sensors and methods that can be used for a BSN for Affective Communication, and enable future immersive health-interactions over the Tactile Internet.**

Keywords—Body Sensor Networks, AI-assisted inference, Affective Communication, non-invasive sensors, Patient-monitoring

I. Introduction

As we develop more robust and non-invasive sensors, our ability to build better Body Sensor Networks (BSNs) that are more likely to be used, increases. Such BSNs will not only aid in reporting on human wellness and help us gauge the effectiveness and responsiveness of treatments, but further feed into the next generation of Affective Computing models that attempt to encode our interactions and relay both conscious and subconscious decisions to cyber physical systems [1].

However, there are many hindrances in the status quo for BSN adoption. While the reasons are largely tied to the type of service, status of the patient, and invasiveness of the BSN being deployed, they largely share similar patterns in lack of adoption. To focus the scope of this paper, and without loss of generality, the spectrum of sensing techniques, their relation to human well-being and responses, along with the metrics used to gauge them, shall be elaborated upon in the special case of mental health monitoring; both during and post-therapy.

Despite high individual and societal costs of mental health issues, treatment remains underutilized or inaccessible, largely due to personal attitudes toward treatment and/or a lack of physical or financial resources to access care [2]. The use of physiological measures to evaluate and demonstrate effectiveness of mental health treatment may aid in addressing barriers. Patients are generally more willing to report and seek treatment for physical symptoms and may be more likely to seek treatment if mental health issues are framed from a physiological perspective.

Further, physiological data provides a more objective assessment of the effectiveness of therapy compared to self-report measures, which largely depend on respondents' abilities to accurately identify and describe their internal states [3]. Finally, consistent, reliable collection of physiological data to demonstrate counseling effectiveness may also lead to improved coverage of mental health services, further reducing financial barriers to treatment.

The rise of non-invasive wearable technology presents an opportunity to improve the feasibility of recording and using physiological data to obtain a more robust evaluation of patient well-being, as well as therapeutic effectiveness. The remainder of this paper reviews physiological indicators of mental health and well-being, sensor types, the spectrum of body sensors, and scales and benchmarks that can be used to corroborate physiological data.

II. Measuring Human responses using BSNs

One of the core challenges in BSN adoption and development by researchers, is carefully associating measured indicators, such as heart rate variation, with individualized responses to different stimuli across different users. We hereby elaborate on the components of the autonomic nervous system that cause different responses and interpret internal body signals, and how we can currently measure such responses, either directly, or through calculated and inferred measures.

A. Measuring Sympathetic vs Parasympathetic responses

The autonomic nervous system consists of the sympathetic and parasympathetic systems, which respectively activate and inhibit the body's stress (fight or flight) response. The insular cortex, or insula, is known as the "hub" of the brain as shown in Figure 1, which processes and integrates information from cognitive, affective, visual, and sensorimotor networks to make an overall determination from the stimuli and generate a corresponding response [4]. When the insula decides a

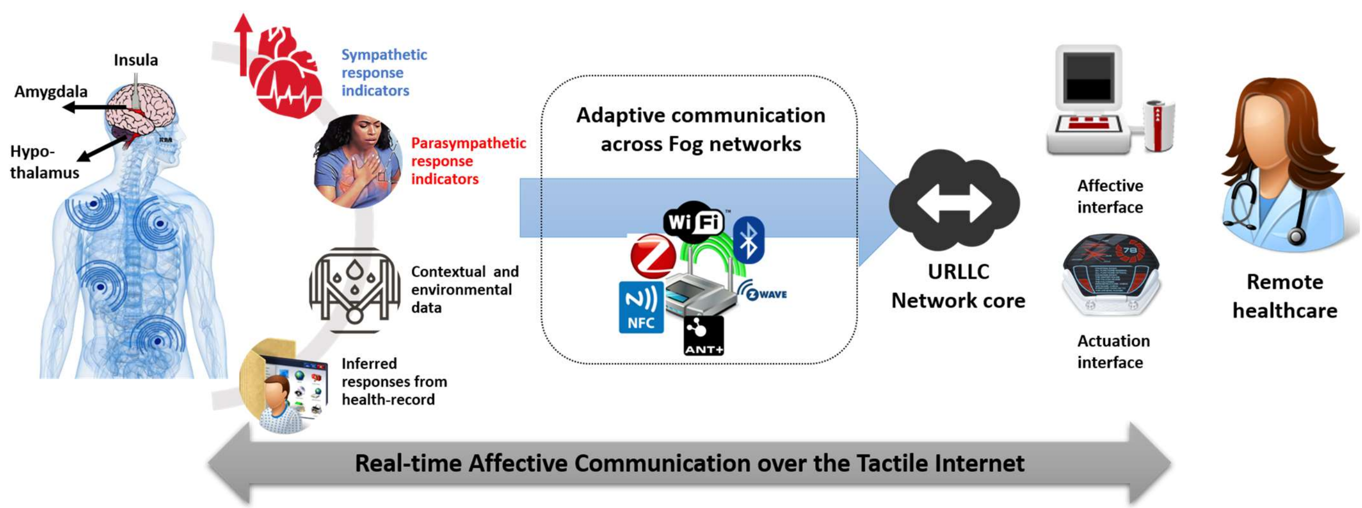

Fig. 1. The role of Body Sensor Networks in identifying, measuring and inferring the responses of the human autonomic nervous system. The overall architecture of how such data points would aggregate to relay Affective Communication between a patient and a healthcare provider, over an Ultra Reliable Low Latency Communication (URLLC) network core, is shown.

situation is threatening, the amygdala sends a signal to the hypothalamus, which signals the adrenal glands to pump the hormone epinephrine, or adrenaline, into the bloodstream. The epinephrine causes physiological changes that prepare the body to respond to a stressor, such as increasing energy, alertness, and oxygen in the bloodstream.

If the stressor remains after the initial surge of epinephrine, the hypothalamus signals to the HPA axis to release the hormone cortisol, which keeps the sympathetic nervous system activated. When the threat subsides, cortisol levels decrease, and the parasympathetic nervous inhibits the stress response [5].

The parasympathetic nervous system consists of four cranial nerves directly connected to the brain. The vagus nerve comprises about 75% of the parasympathetic nervous system. The three remaining nerves associated with the parasympathetic nervous system connect to the eyes, nose, and mouth. These are critical responses that can capture Affective communication over the Tactile Internet [6].

Activation of the sympathetic nervous system is beneficial for increasing energy, alertness, and productivity that may be needed to address an acute stressor. However, chronic activation of the sympathetic nervous system has been shown to lead to poor mental and physical health outcomes, including hypertension, heart disease, anxiety, and depression [7].

In the remainder of this section we elaborate on the different types of measurable responses of the human body, and whether they could be directly measured, calculated from direct measurements, or inferred from different responses.

B. Measured indicators

Physiological indicators can be directly measured to assess changes in well-being include heart rate (HR), blood volume pulse (BVP), respiration rate (RR), perspiration, blood pressure (BP), and skin temperature (ST). Activation of the sympathetic nervous system increases HR, BVP, RR, perspiration, and BP and decreases ST [5].

C. Calculated indicators

1) Emotion regulation via heart rate variability (HRV): HRV is defined as the degree of variation in time between each heartbeat and has received particular attention as a physiological indicator of emotion regulation. HRV measures the parasympathetic nervous system's ability to appropriately regulate sympathetic nervous system activity in the absence of threat and/or presence of inter- and intrapersonal safety cues. The simultaneous engagement of the sympathetic and parasympathetic nervous system leads to variation in the time between each heartbeat, with greater variation indicating greater ability to regulate sympathetic activity. On the other hand, in the presence of threat and absence of safety cues, the parasympathetic nervous system is disengaged, allowing the sympathetic nervous system to speed up heart rate, leading to decreased HRV [3].

Prior research has demonstrated the associations between HRV and positive physical, psychological, and therapeutic outcomes, including reduced risk for cardiovascular disease, improved cognitive performance, lower symptom severity in patients with depression, improved emotional awareness and regulation, and decreased likelihood of early therapy termination and residual anxiety disorder symptoms, as surveyed in [3]. Furthermore, biofeedback interventions aimed at improving HRV have been shown to improve mental health symptoms.

A meta-analysis by Goessl and colleagues [8] of 24 studies found that HRV biofeedback training without another active treatment was associated with a large reduction in self-reported stress and anxiety (Hedges' g pre-post within group effect size = 0.81). Similarly, Caldwell and Steffan [9] found that combining HRV biofeedback with psychotherapy for major depressive disorder produced a larger decrease in depressive symptoms and a larger increase in HRV compared to a psychotherapy only group and a non-depressed control group, which received no intervention.

A typical heartbeat has four elements, including baseline, P wave, QRS complex, and T wave. The R "peak" of the beat is most distinctive and is used to calculate the interbeat interval, or the time between successive R peaks [7]. HRV can be calculated from the interbeat interval (IBI), and has both time and frequency domain measures. Prior research indicates time domain measures are most robust in stress detection [5] and include the root mean square (RMSSD) and standard deviation of normal-to-normal (SDNN) intervals between successive heartbeats (i.e., R-R peaks) [9]. Frequency domain measures include low frequency (LF) and high frequency (HF) spectral power, or the power of the low-frequency band (0.05 - 0.15 Hz) and high frequency band (0.15-0.40 Hz), respectively [9]. Activity in the LF range reflects sympathetic arousal, while the ratio of LF to HF frequency is seen as an index of sympathetic to parasympathetic activity, with a lower ratio indicating higher HRV [10]. HF is also known as respiratory sinus arrhythmia (RSA) due to the influence of respiration on IBI variance and represents parasympathetic nervous system regulation almost exclusively [11].

Therapeutic alliance via therapeutic index: Research has shown that the therapeutic alliance, or the bond between the patient and therapist and extent to which they agree on the goals and tasks to achieve those goals, as rated by the therapist and patient, is associated with the extent of engagement in therapy and reduction of global mental health symptoms and psychotic symptoms. The relationship between the therapeutic alliance and HRV is supported by the Polyvagal theory, which asserts that as the therapeutic alliance develops, the patient's perception of safety within the counseling environment should increase, thus leading to increased HRV [3] [10]. The authors in [10] calculated a therapeutic index (TI) using the "natural logarithmic value of the ratio of the sum of the positive skin conductance resonance values, divided by the absolute sum of the negative values". The authors obtained the highest TI across three-minute segments of the session, with higher TI indicating greater therapist and patient concordance and a better therapeutic alliance [10].

D. Inferred indicators

1) Emotional state via facial expressions: Extensive research has been conducted to identify emotions based on facial recognition both "in the wild" and in more controlled settings. The authors in [12] detailed the methods they used to train and identify the best multi-modal approaches for emotion recognition in the wild using various datasets. They obtained features using a deep convolutional neural network model that was pre-trained for facial recognition and then fine tuned with the FER 2013 emotion corpus dataset.

Dense and audio features were also obtained, and these features were fed into kernel extreme learning machine and partial least squares regression classification models, and applied weighted score fusion for each model and class [12]. Further details can be found in [12]. This approach won the ChaLearn-LAP First Impressions Challenge in 2016 with an average accuracy level of 0.913.

2) Emotional state via behavioral indicators: Behavioral indicators, such as speech pitch and tone, body movements and gestures, keystroke and mouse patterns, and mobile phone usage have also been used to infer stress, as elaborated upon in the work of Can et al. [7].

III. Sensor Types

There are a number of sensors developed specifically to measure indicators of well-being on human subjects, with varying levels of accuracy, precision and invasiveness. In this section we elaborate on leading techniques for yielding such indicators, and how they operate.

A. Photoplethysmography (PPG):

PPG measures blood volume pulse (BVP), or the the volume of blood that passes through tissues. A PPG is a less invasive sensor that can be imbedded in a wrist worn device, but is more sensitive to movement and prone to measurement errors or missing data than an ECG [11]. While both HR and BVP reflect cardiac activity, they are different in that BVP can be influenced by any physiological event that may affect the time between the emission of the electrical signal from the heart to when the blood circulates and reaches the location of the PPG sensor.

B. Electrocardiograph (ECG):

An ECG uses sensors to measure heart rate by capturing the heart's electrical signals via electrodes placed on the chest or on the left arm, right arm, and left leg [7]. ECGs are less sensitive to movement and more accurate but generally require more invasive and/or inconvenient placement of sensors underneath clothes and may require setup by an expert (see Table 1 below) [11].

C. Galvanic Skin Response

Galvanic Skin Response (GSR) sensors assess changes in sweat gland activity by emitting a small current and measuring skin resistance between two electrodes. The sensors can be imbedded in wrist worn devices, or collected via sensors placed on the palms, chest, or fingers [7].

D. Skin Temperature & Respiration

Temperature sensors can be embedded in wearable devices to measure skin temperature. Changes in blood flow with the activation of the sympathetic nervous system tend to result in a decrease in skin temperature by approximately 0.1 or 0.2 °C [7].

Respiration rate is typically measured by sensors that are placed on the chest or abdomen to measure expansion and contraction, which is exhaustively elaborated upon in [13].

E. Acceleration (ACC) and gyroscope

Both ACC and gyroscope sensors measure physical activity and/or body movement and are commonly included in wearable devices and mobile phones. An ACC sensor measures linear acceleration and a gyroscope measures angular velocity. These sensors can be used to measure movement and provide context to differentiate changes in sensor measurements that do not reflect change in stress level or emotions (e.g., when participants are exercising) [5]. ACC sensors can also be placed on the lower leg or foot or embedded in smart footwear

TABLE I. A COMPARISON OF BSNs

Device Type	Product Example	Sensor Options	Sampling Rate	Battery Life	Size
Wrist band	Empatica Embrace Plus	PPG, EDA, ST, ACC, Gyroscope	PPG: 64 Hz ACC: 32 Hz EDA, ST: 64 Hz	Up to 7 days	32x32x15mm
Wrist band + wired finger sensors	Verisense Pulse+	PPG, EDA, ACC, Gyroscope	PPG: 50-400 Hz ACC: 12.5-100 Hz EDA: 5.1-51.2 Hz	Up to 6 months	35x43x12mm
Chest Strap	Polar H10	ECG, RR, ACC, ST	ECG: 1000 Hz	Up to 400 hours	65x34x10mm
Chest patch electrode	Plux Biosignals CardioBAN	ECG, RR, ACC, Gyroscope	Up to 1000 Hz per channel	Up to 4 hours	28x70x12 mm
Chest and palm electrodes wired to mobile device	MindWare Mobile	EKG, EDA, RR, EMG, ACC	500 Hz per channel	Up to 48 hours	117x79x47mm
Implanted cardiac monitor	LUX-Dx ICM Device	ECG	Unidentified	3 years	7.2x44.8x4.0mm

or bracelets to measure movement and conduct gait analysis, which can be used to detect change in mental state [14].

F. *Audio Recordings*

Audio recordings can also be used to detect emotion and well-being. Voice, including tone, pitch, intensity, and rate of speech, as well as non-voice (e.g., silence and noise) can be used to extract features to identify stress and emotions and/or provide context for other sensors. Tools such as the openSMILE library have been developed to perform feature extraction and classification for use in emotion recognition. In daily life settings, audio data are typically captured via smartphones [7] [12].

G. *Image and Video Recordings*

Image and video recordings capture facial expressions, gestures, and body movement, which can be used to extract features to identify emotions as described in Section II. D., combined with other data to improve accuracy, and/or provide context for other sensors [7] [12].

IV. THE SPECTRUM OF BODY SENSORS BY INVASIVENESS

In this section we cover different types of sensors and how they are worn, in order from least to most invasive. Table 1 above provides specific details on an example product for each device type.

A. *Wrist/finger devices*

A wrist worn device is the least invasive BSN that has contact with the body. These devices typically house one or more sensors, including PPG, GSR, ST, and/or ACC sensors. Newer models are water and impact resistant and have a battery life of between four days to six months, which allows for the device to be worn during more activities and for a longer period prior to needing a recharge than other device types. Devices may also allow for wireless and automatic data upload and remote tracking for patient compliance. Prior studies have found that wrist band PPG sensors combined with data processing software can produce highly accurate IBI measurements [11]. However, the PPG sensor is more sensitive to movement than ECG sensors, resulting in increased missing data and lower accuracy for HRV. The device can be worn on the non-dominant palm to partially address movement concerns. In addition, studies have found that wrist worn devices do not produce reliable GSR data [11]. Nevertheless, machine learning algorithms deployed on wrist worn device data have been shown to detect stress levels with accuracies ranging between 60 to 99 percent [7].

Wrist devices can also include finger sensors that wrap around the base of the index and middle fingers and attach to the wrist device with a small cord. This device is somewhat more invasive due to the cord that may hinder use of the hand; however, the addition of finger sensors can increase the accuracy of HR and GSR.

B. *Chest straps/patches*

Chest straps are the next least-invasive device type and are more invasive than wrist devices because they must be worn under clothing and may be less comfortable. However, once applied, they generally do not inhibit movement and daily activities. Devices can be water resistant and have a battery life of between 35 to 400 hours.

Chest straps typically house ECG sensors, and may also include RR, ACC, and ST sensors. The location of the chest strap near the heart is less sensitive to movement and allows for greater accuracy of HR and HRV data. A similar device, the chest patch, has also previously been used in research to record ECG, RR, ACC, and gyroscope measurements, and provide similar accuracy to chest straps. The device may have a shorter battery life and require gelled electrodes to be adhered to the body, making it somewhat more difficult to set up, but allows mobility similar to chest straps once applied.

C. *Mobile electrode devices*

Other studies have used devices where electrodes are applied by experts to the chest, back, and/or palm to collect ECG, EDA, RR and/or ACC measurements, with wires that connect to a mobile device that can be worn under clothing. While these devices may not significantly impede daily activities, they are more invasive than the wireless wrist and chest devices. They are also generally not water resistant and have a somewhat shorter battery life of between 24 to up to 400 hours. However, these devices are highly accurate and considered the "gold standard" by which other device measurements are compared.

D. Implanted devices

Finally, the most invasive type of body sensors involves devices that can be implanted into vessels, under the skin, or into the eye to measure physiological parameters, such as blood pressure, heart rate, glucose, joint strain, and neurological signals. These devices need to be implanted by a doctor via an injection or minor surgery. The authors in [15] provide a review of the current technologies and challenges of implantable devices, including wireless communication methods, security concerns, and power sources.

V. Scales and Benchmarks for assessing BSN feedback

Since many of the measured responses and indicators of well-being are estimated from a variety of sensors with inherent discrepancies, it is critical to contrast their results with benchmarks that are used more traditionally to predict the mental/health state of an individual. We hereby elaborate on different benchmarks adopted by healthcare professionals to assess the well-being of patients and users and discuss their efficacy as robust standards. The authors in [16] and [17] provide a comprehensive review of measures used to assess anxiety and depression.

A. Stress

1) Perceived Stress Scale (PSS): The PSS is a global stress scale that asks respondents to rate on a scale of 0 to 4 how often they felt a certain way during the last month. The original survey consists of 14 questions, demonstrated adequate reliability and was found to measure a construct distinct from depression. A four-item version had moderate loss in internal reliability compared to the original version, but was found to have acceptable psychometric properties and is useful in assessment settings where time is limited [18].

B. Depression

1) Beck Depression Inventory-II (BDI-II): The BDI-II is a 21-item measure that asks respondents to rate their experience of symptoms of depression within the past two weeks on a four-point scale. Self-administration of the scale takes between five to ten minutes to complete. The BDI-II was developed to align with the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition (DSM-IV) criteria and is one of three instruments endorsed by the National Institute for Health and Clinical Excellence for use in primary care to assess baseline and post-treatment severity of depression [16]. The BDI-II demonstrates strong psychometric properties [16].

2) Center for Epidemiologic Studies Depression Scale (CES-D): The CES-D is a 20-item measure used to assess depressive symptoms in the general population. Respondents are asked to rate how often they experienced symptoms of depression over the past week, and the scale takes about ten minutes to complete [16]. The CES-D has been widely tested and found to be reliable and valid in multiple populations [16].

3) Patient Health Questionnaire (PHQ-9): The PHQ-9 is a nine-item measure used to assess depression in clinical settings and populations and is based on the DSM-IV criteria for depression. The PHQ-9 asks respondents to rate on a four-point scale the degree of severity of symptoms and takes less than three minutes to complete [16]. The PHQ-9 demonstrates good reliability and validity, and a reduction of five or more points indicates significant reduction in depression or response to treatment [16].

C. Anxiety

1) Beck Anxiety Inventory (BAI): The BAI is a 21-item measure used to assess anxiety symptoms on a four-point scale over the past week. The BAI can be completed in between five to ten minutes, demonstrates good psychometric properties, and is sensitive to change [17].

2) State-Trait Anxiety Inventory (STAI): The STAI is a 40-item questionnaire used to assess current feelings of anxiety (20 questions; state anxiety subscale) and more general aspects of a tendency toward anxiety (20 questions; trait anxiety subscale) [7]. Respondents are asked to consider their feelings “at the moment” for the state anxiety subscale and “in general” for the trait anxiety subscale on a four-point scale and takes about ten minutes to complete [17].

D. Therapeutic Alliance

1) Working Alliance Inventory-Short Revised (WAI-SR): The WAI-SR [19] is a revision of the Working Alliance Inventory and the Working Alliance Inventory-Short and was found to better differentiate the factor structures of client and therapist agreement on goals, client’s agreement with the therapist on the tasks to address the goals, and the quality of their bond [19].

E. Affect studies

1) Positive and Negative Affect Schedule (PANAS): The PANAS is a 20-item measure used to assess the extent to which an individual experiences positive or pleasurable and negative or unpleasurable experiences with the environment. The PANAS was found to be a valid and reliable measure of positive and negative affect in a large non-clinical sample [20].

2) Self-Assessment Manikin (SAM): The SAM has three domains, including valence, arousal, and dominance and has been used to improve accuracy in a speech emotion recognition system by up to 2.95% [21].

F. Combined Assessments

1) Depression Anxiety Stress Scales (DASS). The DASS was originally created as a 42-item measure that asks participants to rate on a 4-point scale the degree to which they experienced each symptom over the past week. The DASS demonstrated satisfactory psychometric properties and correlations of 0.81 with the BAI and 0.74 with the BDI. The measure was later shortened to 21 items [16] with chronbach’s alpha of between 0.82 to 0.93 for the depression, anxiety, stress, and total scales, representing a more general aspect of psychological distress or negative affect [16].

2) Hospital Anxiety and Depression Scale (HADS): The HADS is a 14-item measure used to assess anxiety (seven items) and depression (seven items) and identify probable cases in a clinical population, but is not used as a diagnostic tool. Respondents are asked to rate their responses on a four-point scale and the measure takes five minutes or less to complete. The HADS demonstrates high reliability and good to very good construct validity [16].

VI. Discussion

Improvements in BSN technologies and the rise in daily use of wearable sensors provide opportunities to measure and gain insight into individual progress in therapy. This work found that HRV is a main indicator used to detect stress or emotional state. Measuring other indicators, such as EDA and facial expressions, concurrently with HRV generally increases detection accuracy.

Our comparative analysis also demonstrated that PPG sensors used in wrist bands have less accurate HRV measurements compared to ECG sensors placed closer to the heart, such as in chest straps, which are somewhat more invasive and currently less widely used. Prior research demonstrated that PPG sensors can be used to detect binary stress/emotional states with accuracies over 90% in laboratory settings; however, the accuracy decreases when trying to distinguish between more than two states and in "daily life" settings over a longer data collection period. Increasing the accuracy of PPG sensors and/or increasing the attractiveness of using ECG chest strap sensors in daily life may improve accuracy under less controlled conditions.

VII. Conclusions and Future Work

As we build towards Affective Communication over the Tactile Internet, it is critical to comprehensively balance the input of different sensors and inference models, that could in aggregation relay the most accurate emotional and physical state of patients and users. This paper presents a building block in identifying the best subset of sensors and methods that can be used for a BSN, tailored to the service in their field.

Future research can build upon this work by establishing a framework to autonomously evaluate the impact of different sensors on measurable responses, and establish a feedback loop to enforce input from the most beneficial sensors (e.g, by increasing their sampling rates) and eventually silencing ones that are not critical, while balancing their responsiveness and invasiveness. Ideally, immersive Tactile Internet interactions based on this system shall aim to assess the effectiveness of sensor pruning and selection schemes in a feedback loop.

Acknowledgment

This work was supported by the Master of Science in Computer Science Consortium's (MSCS) Distributed Research Apprenticeships for Master's (DREAM) Program.

References

[1] R. El Kaliouby, P. Turcot, F. Handford, D. Bender, R. Picard, R. Sadowsky and O. Wilder-Smith. "Affect usage within a gaming context." U.S. Patent 10,843,078, issued November 24, 2020.

[2] L. Andrade, J. Alonso, Z. Mneimneh, J. Wells, A. Al-Hamzawi, G. Borges, "Barriers to mental health treatment: results from the WHO World Mental Health surveys," Psychological Medicine, vol. 44, pp. 1303-1317, 2014.

[3] N. Petrocchi and S. Cheli, "The social brain and heart rate variability: implications of psychotherapy," Psychology and Psychotherapy: Theory, Research, and Practice, vol. 92, pp. 208-223, 2019.

[4] M. Balban, E. Cafaro, L. Fletcher, M. Washington, M. Bijanzadeh, A. Lee, E. Chang and A. Huberman, "Human responses to visually evoked threat." *Current biology,* Vol. 31, Iss. 3, pp. 601–612, 2021.

[5] S. Gedam and S. Paul, "A review on mental stress detection using wearable sensors and machine learning techniques," IEEE Access, vol. 9, pp. 84045-84066, 2021.

[6] S. Oteafy and H. Hassanein, "Leveraging Tactile Internet Cognizance and Operation via IoT and Edge Technologies," in Proceedings of the IEEE, vol. 107, no. 2, pp. 364-375, Feb. 2019.

[7] Y. Can, B. Arnrich, and C. Ersoy, "Stress detection in daily life scenarios using smart phones and wearable sensors: a survey," Journal of Biomedical Informatics, vol. 92, p. 103039, 2019.

[8] V. Goessl, J. Curtiss, and S. Hofmann, "The effect of heart rate variability biofeedback training on stress and anxiety: a meta-analysis," Psychological Medicine, vol. 47, pp. 2578-2586, 2017.

[9] Y. Caldwell and P. Steffen, "Adding HRV biofeedback to psychotherapy increases heart rate variability and improves the treatment of major depressive disorder," International Journal of Psychophysiology, vol. 131, pp. 96-101, 2018.

[10] T. Stratford, A. Meara, and S. Lal, "Heart rate variability and the anxious client cardiac autonomic and behavioral associations with therapeutic alliance," J Nerv. Ment. Dis., vol. 202, pp. 613-619, 2014.

[11] N. Milstein and I. Gordon, "Validating Measures of Electrodermal Activity and Heart Rate Variability Dervied from the Empatica E4 Utilized in Research Settings That Involve Interactive Dyadic States," Front. Behav. Neurosci., vol 14, p. 148, 2020.

[12] H. Kaya, F. Gurpinar, and A. Salah, "Video-based emotion recognition in the wild using deep transfer learning and score fusion," Image and Vision Computing, vol. 65, pp. 66-75, 2017.

[13] E. Vanegas, R. Igual, and I. Plaza, "Sensing systems for respiration monitoring: a technical systematic review," Sensors (Basel), vol. 20, p. PMC757-710, Sep. 2020.

[14] Y. Tao, H. Qian, and Y. Xu, "Affection sensing in gait using intelligent shoe system," 2014 4th IEEE International Conference on Information Science and Technology, pp. 764-767, 2014.

[15] B. Nelson, S. Karipott, Y. Wang, and K. Ong, "Wireless technologies for implantable devices," Sensors, p. 4604, 2020.

[16] K. Smarr and A. Keefer, "Measures of Depression and Depressive Symptoms," Arthritis Care & Research, vol. 63, pp. S454-S466, November, 2011.

[17] L. Julian, "Measures of Anxiety," Arthritis Care & Research, vol. 63, pp. S467-S472, 2011.

[18] S. Warttig, M. Forshaw, J. South, and A. White, "New, normative, English-sample data for the short form perceived stress scale (PSS-4)," Journal of Health Psychology, vol. 18, pp. 1617-1628, 2013.

[19] T. Munder, F. Wilmers, R. Leonhart, H. Linster, and J. Barth, "Working alliance inventory-short revised (WAI-SR): psychometric properties in outpatients and inpatients," Clinical psychology and psychotherapy, vol. 17, pp 231-239, 2010.

[20] J. Crawford and J. Henry, "The positive and negative affect schedule (PANAS): construct validity, measurement properties and normative data in a large non-clinical sample," British Journal of Clinical Psychology, vol. 43, pp. 245-265, 2004.

[21] J.-M. Chen, P.-C. Chang, and K.-W. Liang, "Speech emotion recognition based on joint self-assessment manikins and emotion labels," 2019 IEEE International Symposium on Multimedia (ISM), pp. 327-3273, 2019.