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A Review of Tools and Methods for Detection, Analysis, and Prediction of Allostatic Load due to Workplace Stress

Karl Magtibay, and Karthikeyan Umapathy, *Senior Member, IEEE,*

Abstract—Chronic stress risks an individual's overall well-being. Chronic stress is associated with allostatic load, the body's wear-and-tear due to prolonged heightened physiological and psychological states. Increased allostatic load among workers increases their risk of injuries and the likelihood of diseases and illnesses. An allostatic load model could explain the basis of a stress response. Stress research in affective computing uses wearable devices, data processing algorithms, and machine learning methods to create models that could benefit from an allostatic load model of stress. We emphasize the need for the allostatic load model in affective computing to create disease and illness prediction models. Predictive models could enhance safeguards in the workplace by helping to create proactive mitigation strategies against chronic stress. First, we briefly introduce allostasis' physiological and psychological basis. Next, we reviewed stress studies within affective computing that may benefit from an allostatic load model of stress. We focused our review on studies conducted in dynamic settings, such as the workplace, and those incorporating typical stress study elements in affective computing. We conclude our review by identifying gaps between affective computing and neuroscientific stress studies and provide recommendations for adopting the allostatic load model of stress.

Index Terms—Stress, emotions, workplace, allostasis, allostatic load, well-being, smart wearables, signal processing, machine learning.

1 Introduction

STRESS is a systemic response of the human body towards a perceived threat, real or imagined, against its overall well-being [1], [2]. Similarly, chronic workplace stress has contributed to the steep rise of incidences of cardiovascular diseases [3], diabetes [4], cancers [5], and mental illnesses [6] among working populations hence, has become an epidemiological problem.

A prolonged heightened state of physiological and psychological functions due to chronic workplace stress results in allostasis [1], [2], [3]. Allostasis causes accelerated wear-and-tear of multiple organ systems (i.e., cardiovascular, cognitive, immune) of the human body, causing increased vulnerability to injuries, diseases, and illnesses [2]. The degree of a person's allostatic state is described with an allostatic load. An allostatic load index is calculated using a collection of clinically-proven biomarkers over long periods, such as cholesterol levels, blood pressure, and waist-hip ratio, as an index of severity for physical and cognitive wear-and-tear [7]. In addition, the allostatic load index also accounts for the contribution of psychological factors of a stress response. For example, chronically stressed persons have tendencies to overeat, which could lead to increased weight and, therefore, increased allostatic load.

High allostatic loads have been implicated through increased medical and psychological disorders among chronically stressed healthcare workers during a pandemic [8], [9] and among underground miners exposed to high temperatures, pollution, and heavy machinery [10]. Increased allostatic loads have also been attributed to decreased cognition and dexterity among workers [11], making them vulnerable to injuries, illnesses, and diseases. A 2019 report by the Association of Worker's Compensation Boards of Canada states that over 270,000 injuries and over 900 fatalities in the workplace occurred between 2017 and 2019, with healthcare and social assistance, manufacturing, and construction as the top 3 industries contributing approximately 42% of reported incidences [12]. While stress reduction strategies have been implemented in many workplaces (i.e., mindfulness and meditation programs), they are reactive. Proactively mitigating allostasis due to chronic workplace stress could enhance safeguards and maintain workers' long-term well-being. Moreover, regular proactive mitigation of allostasis due to chronic stress may decrease workers' likelihood of developing life-threatening diseases later in life.

Affordable and ubiquitous wearable devices within a robust machine-learning framework could be used to mitigate allostasis due to chronic workplace stress proactively. Physiological signals from wearable devices, such as electrocardiograms (ECGs) and electrodermal activity (EDA), could indicate stress-induced autonomic responses. Moreover, data features from physiological signals could be treated as equivalents to traditional stress biomarkers. Then, a combination of physiological signal features and psychological data could be used to calculate the allostatic load index in ambulatory settings. Moreover, machine learning algorithms could reveal physiologic response patterns and

- *K. Magtibay is with the Faculty of Engineering and Architectural Sciences, Toronto Metropolitan University (formerly Ryerson University), Toronto, Ontario, Canada, M5B 2K3.*
  E-mail: karl.magtibay@torontomu.ca
- *K. Umapathy is with the Department of Electrical, Computer, and Biomedical Engineering, Toronto Metropolitan University (formerly Ryerson University), Toronto, Ontario, Canada, M5B 2K3.*

behavioural tendencies due to increased allostatic loads. The combination of the tools above could aid in developing and enforcing proactive mitigation strategies against chronic workplace stress and minimize the long-term effects of diseases caused by allostasis.

Within affective computing, studies in workplace stress detection prioritize acute manifestations of stress [13] [14] [15], and few studies examine the effects of chronic workplace stress [16] [17] [18]. Limited studies relate chronic workplace stress to high allostatic loads and the gradual development of illnesses and diseases. The concepts of allostasis and allostatic load have yet to permeate the literature of affective computing, as evident from recent literature surveys [19], [20], [21], [22], despite being widely accepted the fields of neuroscience, psychiatry, and psychology [23], [24].

Since allostasis due to chronic workplace stress is heterogeneous, gradual, and cumulative, it requires robust, multi-faceted tools for evaluation. An allostatic load model of stress provides a holistic description of an individual's response to chronic stress. Furthermore, an allostatic load model of stress accounts for an individual's physical and behavioural patterns and could provide a risk measure for pathologies due to chronic stress. Therefore, we aim to emphasize the need and relevance of incorporating the allostatic load model of stress into affective computing to study allostasis due to chronic workplace stress.

Existing chronic workplace stress studies in affective computing could be augmented by adopting elements of the allostatic load model of stress as follows. First, similar to traditional stress biomarkers, data features extracted from physiological signals must have clinical significance to stress. Second, behavioural tendencies and contextual information could be used with physiological data to improve the detection of stress and analysis of allostatic load. Third, data collection periods could be extended beyond currently implemented durations due to the gradual and cumulative nature of diseases and illnesses. Finally, an allostatic load model of stress could be tuned specifically to an individual's unique stress response.

We review recent studies on workplace stress that could benefit from the allostatic load model. First, we discuss allostasis' physiological and psychological basis and the specific stress biomarkers used to measure it. Second, we review relevant tools and methods used to study workplace stress divided into three sections: physiological signals and behavioural patterns, data feature equivalents of stress biomarkers, and machine learning methods for allostatic load model development. Finally, we provide recommendations for adopting the allostatic load model of stress in affective computing to bridge its gap with established concepts from neuroscience.

2 Allostasis, the Allostatic Load Model, and Workplace Stress

In this section, we introduce the concept of allostasis and differentiate it from the traditional physiologic mechanism of homeostasis. Then, we provide an overview of the systems that make up the allostatic load model to explain the basis of allostasis further. Lastly, we provide background information on how an allostatic load is measured and how it could be related to chronic workplace stress.

2.1 Homeostasis and Allostasis

Homeostasis is a state of equilibrium within living organisms to maintain physiological stability [25]. The primary homeostatic mechanism is the negative feedback loop, ensuring physiological parameters are within a normal range. An example of homeostasis is maintaining core body temperature at 37 °C in response to cold weather. The concept of homeostasis has been instrumental in studying the physiological mechanisms of organ systems. However, neuroscientists Sterling and Eyer did not find the homeostatic model as a sufficient explanation for the elevated but stable cardiovascular response from cohorts exposed to psychosocial and socioeconomic stresses, such as familial loss or prolonged unemployment [26]. The concept of allostasis was therefore introduced.

Allostasis is the continuous adaptation of an organism to maintain systemic stability in the presence of stressors. An example of allostasis is the flexibility of the human cardiovascular system to adjust systolic and diastolic pressures throughout a day depending on environmental demands [26]. While homeostasis demands that systolic and diastolic blood pressure be maintained at a 'normal' level (i.e., approximately 120/80 mmHg), it is not physiologically practical to maintain the same blood pressure level for different types of activities requiring other demands. Instead, the body must continually adapt its physiological parameters to appropriate levels to respond sufficiently to challenges or threats against its well-being.

However, stability does not necessarily mean health. The body operates within a range dictated by the nature of its physiological systems. Sustained operation outside such range could result in diseases, such as hypertension which could be a symptom of diabetes or atherosclerosis. Likewise, repeated and prolonged exposure to stressors strains an organism's physiological systems due to allostasis. This physiological wear-and-tear, the price of adaptation, was formally coined by McEwen and Stellar as the allostatic load [2].

2.2 The Allostatic Load Model

The allostatic load model describes the psychophysiological systems responsible for allostasis [2], [27]. Figure 1 shows a recreated diagram of the allostatic load model. The allostatic load model is divided into two major systems: psychologic and physiologic.

2.2.1 Psychologic System - Appraisal & Behavioural Response

An interpreter's past experiences, genetic predisposition, environmental context, and socioeconomic status influence their stress response. Within the brain, a stressor is processed in the hippocampus for contextual memory storage and the amygdala for threat assessment.

No allostatic response will be induced if the stimulus is assessed as non-threatening. However, its source would be sought if the stimulus is identified as a threat. If the threat source is unknown, an individual will undergo a

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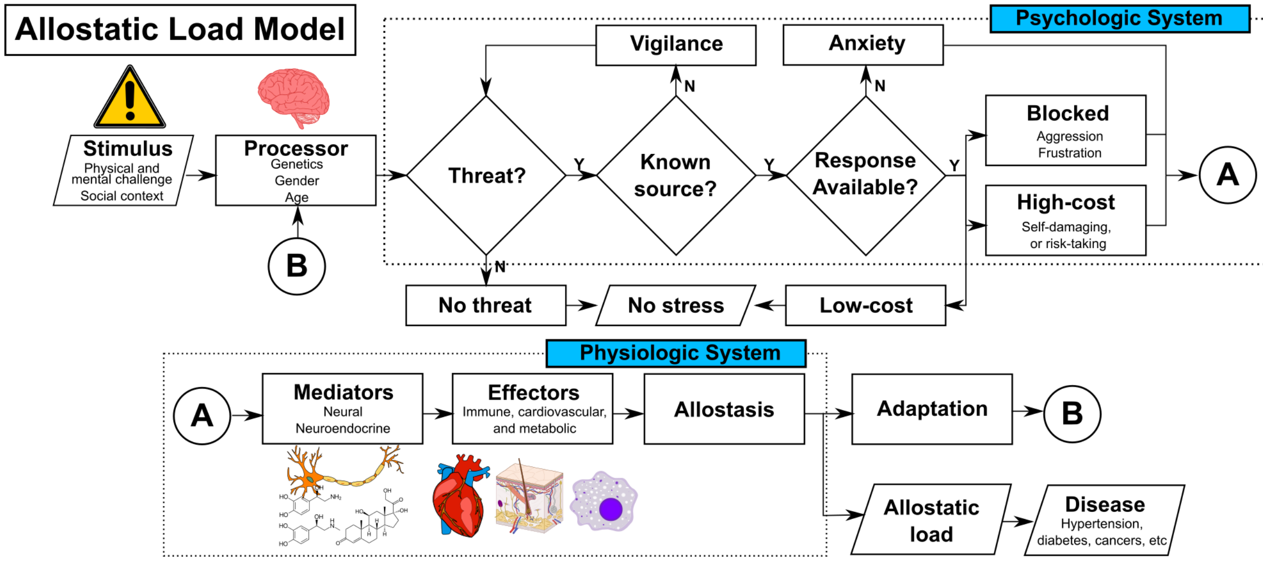

Fig. 1: Flowchart representing the allostatic load model of stress, conceptualized by McEwen and Stellar [2] [27], and illustrated in this work. The flowchart shows physiological and psychological responses to threats or challenges against health and overall well-being and how the body's psychologic and physiologic systems respond and adapt to the presence of stressors. Images (skin by N. Ondrej, and macrophage by A. Rad) adapted in this figure were obtained under the creative commons license (CC BY-ND 4.0).

recurring state of heightened vigilance and may take a high-cost response.

If available, a response to a threat is mounted once identified. A response could be low-cost, producing no stress response. Conversely, a response could be high-cost, demonstrated through aggression, risky behavior, and self-damaging actions (i.e., substance abuse). However, a response could also be hindered such that the threat evokes feelings of helplessness or frustration that could evolve into a high-cost response. Interpretation and reaction to an external stressor thus cascade to a physiological response exhibited through different organ systems.

2.2.2 Physiologic System - The Sympathetic-Adreno-Medullar and The Hypothalamic-Pituitary-Adrenal Axes

The sympatho-adreno-medullar (SAM) and hypothalamic-pituitary-adrenal (HPA) axes of the neuroendocrine system are responsible for initiating and mounting a physical stress response [7]. Activation of the SAM axis promotes the release of catecholamines, including adrenaline and norepinephrine. Thus, the body can rapidly respond to acute stressors, initiating a fight-or-flight response by increasing cardiac output, heart rate, and blood flow to skeletal muscles while decreasing blood flow to the gut and peripheral organs.

The HPA axis is the primary mediator of physiologic responses under the allostatic load model [7], [28]. Activation of the HPA axis induces synthesis, release, and regulation of glucocorticoids into the bloodstream, one of which is cortisol: the primary stress hormone [28]. In response to stressors, cortisol increases the availability of blood glucose as an energy source for the brain, skeletal, and cardiac muscles through gluconeogenesis in the liver, insulin inhibition, and glucagon production from the pancreas. Cortisol also aids in increasing fat and protein metabolism to support the energy requirements of a fight-or-flight response. Lastly, cortisol reduces the immune system's inflammatory response associated with histamine and cytokine secretions during a stress response. The HPA axis also supports the long-term or sustained response to stressors.

The brain has receptors for neuroendocrine biomolecules released by the SAM and HPA axes [29], [30]. Using information fed back to the central and peripheral nervous systems, psychologic and physiologic components of the allostatic model adapt or habituate to any external changes. However, sustained over-activation of the SAM and HPA axes has detrimental effects on the body. For example, repeated exposure to intense stress causes atrophy of specific hippocampus regions [2], [28], interfering with the storage and retrieval of contextual memories. Failure to retrieve stored contextual memories could lead to an inappropriate or disproportionate assessment of stressors, affecting an individual's stress response. Similarly, catecholamines and glucocorticoids released to the bloodstream by the HPA and SAM axes increase an individual's overall blood pressure. Prolonged glucose elevation could develop into diabetes [23], [31], accelerate the development of atherosclerosis and other cardiovascular diseases [23], [32].

2.2.3 Workplace Stress, Stress Biomarkers, & The Allostatic Load Index

Continued exposure to stressors has been long associated with allostasis, dating back to the observations made by Sterling and Eyer on baby boomers who entered the labor market in the 1960s. As a result of exposure to competition and significant social disruption, allostasis made workers vulnerable to renal, cerebral, and cardiovascular diseases [26]. The accumulation of clinically-relevant stress biomarkers could indicate allostasis. Furthermore, the increased presence of stress biomarkers within the body could be symptoms of underlying medical or psychological issues.

Stress biomarkers could be categorized into primary and secondary. Primary stress biomarkers are biomolecules released from activated physiologic systems to help the body respond adequately. For example, where the SAM and HPA axes belong, the neuroendocrine system releases catecholamines and glucocorticoids as primary stress biomarkers. Similarly, pro- and anti-inflammatory cytokines could synergize with the molecules of the SAM and HPA axes to encourage allostasis [7].

Target organ systems, in turn, respond and adapt to the demands of a stress response to maintain overall stability. The cascaded cardiovascular, respiratory, metabolic, and immune reaction provides secondary stress biomarkers [7]. For example, increased metabolic function, indicated by the rise of insulin, glucagon, glucose, and cholesterol in the blood, leads to increased blood pressure as a response to stress. Likewise, increased cardiac output, heart rate, and the release of immune proteins also increase blood pressure. However, prolonged elevation of blood pressure could compromise an individual's cardiovascular fitness. On the other hand, metabolic dysfunction could result in general weight changes and body morphology, which are evaluated with anthropometric measures, such as body mass index (BMI) and waist-hip ratio [7] [23].

Stress biomarkers could be used to calculate the allostatic load index or the likelihood of disease or illnesses due to chronic stress. The allostatic load index was developed by Seeman et al. to indicate the gradual and cumulative effects of chronic stress on an aging population using stress biomarkers [33].

Seeman first proposed to calculate an allostatic load index by including the following stress biomarkers that could reflect the harmful effects of chronic stress on the cardiovascular, metabolic, and nervous systems: systolic and diastolic blood pressure, waist-hip ratio, serum high-density lipoprotein (HDL) and total cholesterol levels, blood plasma levels of total glycosylated hemoglobin, serum dehydroepiandrosterone sulfate, 12-hour urinary cortisol excretion, 12-hour urinary norepinephrine, and epinephrine excretion levels. Each stress biomarker is weighted equally and binarily scored based on a patient's quartile placement. If a patient's stress biomarker level is placed at the extreme top or bottom quartile of the sample, that stress biomarker is scored 1 and 0 otherwise. Next, stress biomarker scores are added, and an allostatic load index out of 10 is generated. Allostatic load indices closer to 10 indicate allostatic overload. The rationale for stress biomarker level thresholds used by Seeman is detailed in their previous work [33].

Studies outside of affective computing frequently use an allostatic load index to measure chronic workplace stress' adverse long-term health effects. Some workplace stress studies have adopted the concept of allostasis and its measure of the allostatic load index, as Mauss et al. showed in their review of allostatic load measurements in the workplace [34]. For example, the work by Dich et al. showed that greater caregiving responsibilities among British civil servants lead to higher allostatic load indices. Dich et al. also showed that workplace stress increased the allostatic effects of high caregiving burden [35]. Another example is the work by Carlsson et al., which showed a significant increase in the allostatic load index among workers involved in county mergers [36]. Carlsson et al.'s work attributed the increase of immune biomarker components, such as interleukin-6 and c-reactive protein, to the increased allostatic load index. Finally, Kerr et al. showed that allostatic load indices in the workplace could differ across genders and occupational gender roles. For example, Kerr et al. found that women in higher positions with greater psychological demands are more resilient to the effects of allostasis than their male counterparts [37].

Mauss et al. noted a lack of agreement in the literature over which combination of stress biomarkers should constitute a gold standard for calculating an allostatic load index. The studies by Dich et al., Carlsson et al., and Kerr et al. used 9, 13, and 23 stress biomarkers, respectively, reflecting the various methods for measuring allostatic load. While researchers agree that neuroendocrine and immunological stress biomarkers should form the foundations of an allostatic load index, variabilities in scoring schemes across studies exist. Mauss' team proposed a streamlined allostatic load index to standardize stress studies, decreasing the number of stress biomarkers to 5 (i.e., diastolic blood pressure, waist circumference, glycosylated hemoglobin, low-density lipoprotein, and heart rate variability) [38]. Although they found these biomarkers highly correlated with established workplace stress models, their proposed method is still gaining traction.

Since the allostatic load model encourages the measurement of physiologic and psychologic stress biomarkers, challenges arise when measurements are made within an ambulatory setting. Measuring stress biomarkers 'in the wild' has been a topic of great discussion in affective computing [39]. While retrieving biospecimens (i.e., saliva, blood, and urine) in a workplace is impractical, they directly indicate SAM and HPA axes activity. Moreover, the measurement alone could become a stressor, hindering workers' functioning. Wearable devices could passively collect and measure external indicators of stress biomarkers non-invasively and unobtrusively. Equivalents of stress biomarkers in physiological and psychological data could be valuable in stress studies under affective computing, especially within a dynamic environment where a subject is ambulatory and are chronically exposed to stressors.

3 Allostatic Load from Wearable Stress Biomarkers

The allostatic load could be measured through stress biomarkers produced by cardiovascular, metabolic, immune, and neuroendocrine systems. Some are used more than others due to organ system interconnection. For example, systolic and diastolic blood pressures and heart rate are stress biomarkers from the cardiovascular system; norepinephrine, epinephrine, dehydroepiandrosterone-sulfate, and cortisol from the neuroendocrine system; triglycerides, total cholesterol, glucose, high-density lipoprotein, glycosylated hemoglobin, and albumin from metabolic activity; and insulin-like growth factor, interleukin-6, fibrinogen, and c-reactive protein from the immune system [7].

Not all stress biomarkers are easily accessible, especially in the workplace, which creates challenges for calculating an allostatic load index for workers. For example, the works reviewed by Mauss et al. required extensive collection and analysis of biological and diary data, which may impede study participation or negatively affect the measurement of allostasis [34]. Thus, equivalents of traditional stress biomarkers could be used to infer allostasis and calculate an allostatic load index. In addition, while we can access cardiovascular stress biomarkers, such as heart rate, oxygen saturation, and systolic and diastolic blood pressures, from physiological signals like electrocardiograph (ECG) and photoplethysmograph (PPG), stress biomarkers from metabolic and neuroendocrine systems could be inferred through signal features of electrodermal activity (EDA). Furthermore, since organ systems sensed by ECG, PPG, and EDA are governed by the autonomic nervous system and are directly influenced by the activities of the SAM and HPA axes, physiological signal features could serve as stress biomarkers equivalents. They could help measure allostatic load due to chronic workplace stress.

In recent years, the rapid advancement of portable, unobtrusive wearable technologies and machine learning techniques have eased the expansion of stress research to dynamic environments. Physiological signals containing stress biomarkers could be collected and analysed almost instantaneously using wearable devices. Moreover, the adoption of wearable devices allowed for real-time monitoring of subjects while minimally encumbered, improving participation in chronic workplace stress studies. Commercialization of some devices improved access to off-the-shelf wearable technologies, providing researchers with streamlined tools for stress research.

While wearable devices could provide real-time information on a person's acute response to stressors, the allostatic load and the likelihoods of diseases and illnesses are better measured over long periods of stress exposure. A collection of stress biomarkers extracted over time could be used to study the gradual development of allostasis and measure changes in a person's allostatic load. Data from wearable devices could be transmitted, stored, and used as sources of stress biomarkers equivalents. Together with psychological data and contextual information, accumulated stress biomarker equivalents could be used with machine learning algorithms to create allostatic load models of stress tailored to an individual or groups of people to aid the detection of allostasis, measurement of allostatic load, and prediction and prevention of potential chronic stress-related diseases.

By adopting the allostatic load model of stress, we could improve current practices for wearable stress detection and disease modeling in affective computing. Not only could we create better stress metrics from equivalents of stress biomarkers, but we may also measure the likelihood of associated diseases emerging from chronic workplace stress. An allostatic load model of stress, augmented with established stress detection methods in affective computing, could provide a way to proactively mitigate the adverse health effects of chronic stress and minimize the likelihood of diseases, illnesses, and injuries in the workplace.

In the following sections, we present a survey of notable studies, both acute and chronic, that could benefit from incorporating elements of the allostatic load model of stress (i.e., behavioural patterns, contextual data, physiologically-relevant signal features, etc.). We included works that use standard elements of stress studies in affective computing, such as wearable technologies, signal feature extraction, and machine learning methods, within the last decade when this review was written. Moreover, we reviewed studies focusing on workplace stress or having implications for worker stress. While the American Psychological Association (APA) have established definitions of acute and chronic stress, they do not include periods of stress exposure to distinguish between acute and chronic stress. In keeping with workplace stress, we defined acute stress as any exposure within a work day (less than 24 hours) and defined chronic stress as otherwise. Our definition accounts for differences in shift lengths and types (i.e., day, afternoon, and night) in different professions.

To indicate the goals and target of each reviewed work, we codified our survey work as follows. First, we assigned a reviewed literature a type A if the work focused on the creation of wearables for data collection and stress monitoring; type B if the work only correlates physiological data to psychological data during stressful tasks; type C if the work aims to classify individuals to stress categories (either binary or tertiary); finally, type D if the work attempts to predict an individual's stress state in the future or provide a stress score/level similar to an allostatic load index.

We summarize the works we reviewed in Table 1. In addition, in Table 2, we provide a list of abbreviations of terms used in existing works to refer to physiological and psychological data and machine learning algorithms.

3.1 Physiological and Psychological Data to Measure Allostatic Load

The allostatic load model provides a physiologic and psychologic basis for a stress response. Therefore, physiological and psychological stress biomarkers could be used to measure allostatic load in the workplace. However, traditional stress biomarkers for measuring the allostatic load index are challenging to access in a dynamic environment. Therefore, we rely on equivalents of traditional stress biomarkers from physiological and psychological data collected with wearable devices. This section presents some data preprocessing and artifact removal techniques, stress-relevant physiological signals, and psychological data included in the reviewed works.

3.1.1 Data Preprocessing and Artifact Removal

Signals from wearable sensors are susceptible to movement artifacts. Movement artifacts are magnified in dynamic environments, such as the workplace, and high-frequency noise or spurious activities could lead to the misidentification of signal features. Before meaningful features can be extracted, raw physiological signals must be preprocessed for noise and artifacts that could negatively affect analysis and prediction models made after that. While there are various methods for different signals and scenarios, we present specific preprocessing and artifact removal methods only from the works we included in our review.

Movement artifacts are usually categorized as low-frequency noise and observed as baseline wanders on raw

TABLE 1: Summary of reviewed works on stress research conducted with smart wearables and wireless body area networks. Each reviewed work is assigned the following codes. Type **A**: the work focused on the creation of wearables for data collection and stress monitoring; Type **B**: the work only correlates physiological data to psychological data during stressful tasks; Type **C** the work aims to classify individuals to stress categories (either binary or tertiary); Finally, type **D** the work attempts to predict an individual's stress state in the future or provide a stress score/level similar to an allostatic load index. Please refer to Table 2 for the list of abbreviations of physiological, psychological, and machine learning terms cited in the table below.

Author	Subject Type	Wearable	Physiological data	Psychological data	Method of Classification or Prediction	Stress Type	Study Code
Aqueveque et al. [13]	Workers	Custom sensors	ECG, RIP, and ST			Acute	A
Awais et al. [40]	General public	Enobio	ECG and EEG	KSS	SVM	Acute	C
Booth et al. [41]	Workers	Garmin vivosmart3	PPG	PSS	EN, RF, GRU, LSTM	Chronic	D
Burghardt et al. [16]	Workers	Fitbit	PPG	ITP, IRB, Big 5, PANAS, substance use, sleep duration	AB, ET, HMM, LR, MLP, RF, and SVM,	Chronic	C
Chalmers et al. [42]	General public	Fitbit	PPG and ECG	DASS, GHQ		Acute	B
Chen et al. [14]	Workers (see Healey et al. [43])	Custom seonsrs (see Healey et al. [43])	ECG, EDA, EMG, and RIP	PSS-like (see Healey et al. [43])	BN, ELM, and SVM	Acute	C
Chen et al. [44]	Workers	E4 Wristband	EDA	VAS		Acute	B
Cho et al. [15]	General public and workers (see Healey et al. [43])	Custom sensors (see Healey et al. [43]) and tabletop sensor	ECG, EDA, EMG, and RIP	DT, PSS-like, and SAM	CNN	Acute	C
Choi et al. [45]	Workers	E4 Wristband	EDA			Chronic	C
Clingan et al. [17]	Workers	Fitbit and Temptraq	PPG and ST	Mood checklist and COVID-19 symptoms		Chronic	A
Coutts et al. [46]	General public	Biobeam	PPG	PSS, DASS, and STAI	LSTM	Chronic	C
Dalmeida et al. [47]	Workers (see Healey et al. [43])	Custom sensors (see Healey et al. [43]) and Apple watch	ECG, EDA, EMG, and RIP	PSS-like (see Healey et al. [43])	GB, KNN, MLP, RF, and SVM	Acute	C
Fazio et al. [48]	Workers	Custom sensors	ACC, PPG, and SPO2			Acute	A
Feng et al. [49]	General public	E4 Wristband	EDA	SAM	SVM	Acute	C
Feng et al. [50]	Workers	Fitbit	PPG	STAI, PANAS, SWLS, Big 5, PSQI, EMA		Chronic	A
Gaballah et al. [51]	Workers	Fitbit, Unihertz Jelly Pro, OMSgnal Smartshirt	ECG and RIP	PSS	bi-LSTM	Chronic	C
Gjoreski et al. [52]	General public	E4 Wristband	PPG, EDA, ST, ACC	STAI, EMA, stress log	KNN, SVM, RF	Chronic	C/D
Heurtefeux et al. [53]	Workers	Custom sensors	ECG and ACC			Acute	A
Hirten et al. [18]	Workers	Apple Watch	PPG	PSS, CDRS, PROMIS, Global health, QoL, and Life orientation test		Chronic	B

TABLE 1: (continued) Summary of reviewed works on stress research conducted with smart wearables and wireless body area networks. Each reviewed work is assigned the following codes. Type **A**: the work focused on the creation of wearables for data collection and stress monitoring; Type **B**: the work only correlates physiological data to psychological data during stressful tasks; Type **C** the work aims to classify individuals to stress categories (either binary or tertiary); Finally, type **D** the work attempts to predict an individual's stress state in the future or provide a stress score/level similar to an allostatic load index. Please refer to Table 2 for the list of abbreviations of physiological, psychological, and machine learning terms cited in the table below.

Author	Subject Type	Wearable	Physiological data	Psychological data	Method of Classification or Prediction	Stress Type	Study Code
Hosseini et al. [54]	Workers	E4 Wristband	PPG, EDA, ST, BVP	custom questionnaire	RF	Chronic	B
Hovsepian et al. [55]	General public	Autosense (see Ertin et al. [56])	ACC, ECG, and RIP	PSS	BN and SVM	Chronic	C/D
Ileri et al. [57]	General public	E4 Wristband and Nonin (see. Birjandtalab et al. [58])	EDA		KNN, MLP, and SVM	Acute	C
Jebelli et al. [59] [60]	Workers	Custom sensor	EEG		DNN, NN and SVM	Acute	C
Kaczor et al. [61]	Workers	E4 Wristband	PPG, EDA, ST	diary, custom questionnaire	DT, LDA, LR, SVM, NN,	Chronic	C
Kent et al. [62]	Workers	Everion	PPG	SUD		Chronic	B
Lee et al. [63]	General public	Non-specific wristband	EDA and PPG	PSS-like	KNN, LR, NN, and SVM	Acute	C
Mozgovoy et al. [64]	Workers	Non-specific wristband	EDA and PPG		k-means, GMM	Chronic	C
Plarre et al. [65]	General public	Autosense (see Etrin et al. [56])	ACC, ECG, EDA, RIP, and ST	Mood checklist	AB, HMM, J48, and SVM	Acute	C/D
Sarker et al. [66]	General public	Custom sensors	ACC, ECG, and RIP	EMA, substance use	RF	Chronic	D
Shukla et al. [67]	Workers (see Healey et al. [43])	Custom sensors (see Healey et al. [43])	EDA	PSS-like	LiR	Acute	D
Smets et al. [68]	Workers	Chillband	ECG, EDA, ST, and ACC	PSS, PSQI, EMA, SAM, DASS	RF	Chronic	C
Smith et al. [69]	Workers	Spirestone	RIP	PSS, MASQ, PANAS	LiR	Chronic	D
Sun et al. [70]	General public	Shimmer	ECG, EDA, and ACC		DT, SVM	Acute	C
Umematsu et al. [71]	General public and Workers	E4 Wristband	ACC, EDA, and ST	PSS and mood checklist	RF	Chronic	C/D
Umematsu et al. [72]	General public	E4 Wristband	ACC, EDA, and ST	Sleep survey	LSTM	Chronic	C/D
Van Kraaij et al. [73]	Workers	Epatch	PPG	PSS	Mixed design modeling	Chronic	B
Wu et al. [74]	Workers	Custom sensors	PPG and ST			Chronic	A
Zhang et al. [75]	Workers	Mbinet Lab Meta Motion			CNN LSTM	Acute	C
Zhuo et al. [76]	Workers	Non-specific oximeter		Insomnia Severity Index		Chronic	B

TABLE 2: Summary of abbreviations for physiological, psychological, and machine learning terms

List of Abbreviations

Physiological data	
ACC	Accelerometer
ECG	Electrocardiogram
EDA	Electrodermal Activity
EEG	Electroencephalograph
EMG	Electromyograph
PPG	Photoplethysmograph
RIP	Respiratory Inductance Plethysmograph
ST	Skin Temperature
Physiological questionnaires	
DASS	Depression, Anxiety, and Stress Levels Scale
DT	Distress Thermometer
EMA	Ecological Momentary Assessment
IRB	In-Role Behaviour
ITP	Individual Task Proficiency
KSS	Karolinska Sleepiness Scale
PANAS	Positive and Negative Affect Schedule
PSQI	Pittsburgh Sleep Quality Index
PSS	Perceived Stress Scale
QoL	Quality of Life
SAM	Self-Assessmemnt Manikins
SSSQ	Short Stress State Questionnaire
STAI	Stress Trait Anxiety Inventory
SUD	Subjective Unites of Distress
VAS	Visual Analog Scale
Machine learning algorithms and statistical models	
AB	Adaptive Boost
BN	Bayesian Network
DNN	Deep Neural Network
ELM	Extreme Machine Learning
ET	Extra Trees
EN	Elastic Net
GMM	Gaussian Mixed Model
GRU	Gated Recurrent Unit
HMM	Hidden Markov Model
LDA	Linear Discriminant Analysis
LR	Logistic Regression
LiR	Linear Regression
LSTM	Long Short-Term Memory
MLP	Multilayer Perceptrons
RF	Random Forest
RNN	Recurrent Neural Network
SVM	Support Vector Machines

signals. ECG signals from custom-made wireless sensor networks, such as those made by Aqueveque et al. [13] and Ertin et al. [56], could be preprocessed using traditional bandpass filters with cutoff frequencies between 5 Hz and 100 Hz. Environmental noise, such as interference from power lines or signal crosstalk due to proximity from other sensors or organ systems, could also affect signal quality. ECG signals could be smoothed to remove random noise using a moving average, or root mean square filter [43], [53], [70] and eliminate specific frequencies with notch filters. Also, artifacts in PPG signals from wearable devices must be removed before feature extraction, as demonstrated by Lee et al. [77] using a simple bandpass filter between 0.5 Hz and 4.0 Hz and by Gjoreski et al. [52] using Winsorization, or the removal of outliers at the extreme percentiles.

A time-series signal, such as inter-beat intervals, calculated from either ECG or PPG signals, could also be prone to artifacts. For example, Van Kraaij et al. [73] used an accelerometer to determine sets of invalid inter-beat intervals due to non-contact electrodes. Furthermore, Van Kraaij's team filtered invalid heart rate data by including values only that are within three standard deviations of a subject's median heart rate and above 30 beats per minute. Filtering physiological data using information from an accelerometer is also a common preprocessing step in stress detection. Periods of intense physical activity could be identified and cross-referenced with segments of physiological data that could be excluded from the stress analysis. For example, in the work of Gjoreski et al. [52], inter-beat intervals temporally aligned with extreme physical activities are excluded from data collection and analysis.

EDA signals are also preprocessed before feature extraction and analysis. While traditional filters are sufficient for some applications, such as a moving average [43], [45], [77] and a highpass filter with a 0.5 Hz cutoff frequency [45], [77], some studies benefited from advanced preprocessing and artifact removal techniques for EDA signals. For example, Lee et al. [63] proposed a cascaded algorithm combining traditional and adaptive filters to preprocess EDA signals collected from construction workers. First, EDA signals are highpass filtered at 0.5 Hz and smoothed using moving average and wavelet filters [67]. Second, respiratory activity from PPG signals was used to identify and remove sections of an EDA signal affected by movement artifacts caused by respiration.

Most current off-the-shelf wearable devices have built-in adaptive filters to preprocess collected signals. Preprocessing and artifact removal minimize disease detection and prediction inaccuracies due to increased allostatic load. Moreover, preprocessing and artifact removal methods ensure only relevant features are included in the analysis of chronic workplace stress, as discussed in the following sections.

3.1.2 Physiological Signals

Traditional stress biomarkers for calculating an allostatic load index are challenging to collect in a dynamic environment such as the workplace. However, ECG, PPG, and EDA signals are accessible with wearable devices. In addition, physiological signals could carry features that reflect the activity of the autonomic nervous system governing the

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SAM and HPA axes. Therefore, features of physiological signals could be used as equivalents to traditional stress biomarkers to assess the progression of allostasis among workers.

The heart's activity is modulated by pacemaker cells innervated by parasympathetic nerves originating from the brain's medulla. The hypothalamus, a significant component of the HPA axis, activates the medulla to modulate a sustained cardiovascular response to stressors [78], [79]. The heart is also innervated by sympathetic nerves, a significant component of the SAM axis, which controls heart rate and blood pressure [78], [79]. Because of its autonomic nature, the heart's activity could be used to infer a stress response. An ECG signal typically represents the heart's electrical activity. In addition, an ECG signal represents the temporal evolution of the heart's electrical activity as it goes through a synchronous contraction and relaxation of its four chambers (i.e., left and right atria, left and right ventricles).

Contraction and relaxation of the heart's chambers also synchronously change pressures. Pressure changes in the heart allow it to pump blood to the lungs for re-oxygenation and to the rest of the body to deliver oxygenated blood to different organ systems. Therefore, changes in the cardiovascular system could be characterized by the systolic and diastolic blood pressures to indicate vascular pressures during contraction and relaxation of the heart chambers, respectively. For example, systolic and diastolic blood pressure and oxygen saturation could be inferred from a PPG signal collected from vascular beds at fingertips or earlobes.

On the other hand, EDA is an electrical signal manifested from skin conductance changes resulting from filling and discharging sweat ducts [80]. EDA is ideally collected from the fingertips (or toe) or palms (foot arch) due to the abundance of sweat glands innervated by nerve fibers of the SNS [80], [81], [82]. While both the HPA and SAM axes contribute to the activation of sweat glands for thermoregulation and emotional stress response, respectively, palmar and plantar sweat glands are activated only by SNS [80], [83]. Hence, dysfunction of the SNS, such as diabetes-induced sweating disorders, could be reflected in an EDA and its features. Moreover, physiological and psychological responses due to a fight-or-flight response against chronic stress could also be indicated with EDA. Due to the autonomic nervous system's influence on ECG, PPG, and EDA signals are excellent sources of physiological equivalents of stress biomarkers from the cardiovascular, metabolic, and neuroendocrine systems.

Devices that provide raw physiological signals allow for the development of robust feature extraction and machine-learning algorithms for chronic stress studies. For example, a study by Aqueveque et al. [13] collected ECG signals, among other signal types, to monitor the overall well-being of high-altitude miners. Due to the harsh working conditions at a high-altitude mine, Aqueveque et al. observed the development of negative social behaviors and disruption to sleep patterns indicative of increased allostatic load. Similarly, the work by Heurtefeux et al. [53] explored the effects of stress on workers in harsh environments. Heurtefeux's team proposed an accurate and energy-efficient wireless sensor network to collect healthcare workers' ECG signals and other data.

Furthermore, raw ECG signals from textile-based sensors were used in a study by Gaballah et al. [51] to detect stress among healthcare workers. A study by de Fazio et al. [48] explores the application of a stand-alone garment carrying a network of wireless physiological and environmental sensors to assess a worker's overall health in harsh environments. Wu et al. [74] also examined the feasibility of wireless sensors to monitor the health and safety of workers.

Using similar devices, Smets et al. [68] collected raw ECG and EDA signals from office workers to study the relationships between workers' physiological stress response, their behavioural patterns, and environmental contexts. Likewise, Sun et al. [70] took advantage of devices that could collect raw ECG and EDA signals. In addition, Sun's team used physiological signal features augmented by contextual data to classify individuals under stress. While the work by Chalmers et al. [42] focused on correlating stress perceptions and physiological stress response, they found that features from raw ECG signals could help indicate developed stress resilience among medical trainees.

A study by Choi et al. [45] tracked the perceived risks by construction workers and their correlation to the raw EDA signal from a wearable device. Although the categorization of risks was done by observers posthoc instead of the workers, Choi's team concluded that an EDA signal could help identify high-risk activities in construction sites. Furthermore, Umematsu et al.'s [71] work with office workers further predicts self-reported well-being complemented with raw EDA signals, among other data types, which could help predict allostatic tendencies and the likelihood of disease among sedentary workers.

Autosense, introduced and developed by Ertin et al. [56], is a compact collection of wireless physiological sensors for continuous data collection, including raw ECG and EDA signals, sent wirelessly to a mobile phone application called Fieldstream for processing and analysis. Groups such as Plarre et al. [65], Hovsepian et al. [55], and Sarker et al. [66] all used Autosense's physiological sensor suite to collect for physiological indicators of a stress response cross-examined with accompanying psychological data. In addition, aggregated data from each group's studies were used to create unique predictive stress models within a dynamic setting.

Raw ECG and EDA signals from truck drivers collected for a study by Healey et al. [43] have been widely used in affective computing. For example, the works by Cho et al. [15], and Dalmeida et al. [47] used an ECG signal, Shukla et al. [67] used an EDA signal from Healey's team. In addition, Chen et al. [14] used both ECG and EDA signals from Healey et al.'s original study to improve stress detection algorithms among drivers. Their studies have significant implications for transportation workers who could become prone to accidents due to long-distance driving without proper rest. Moreover, the passive nature of long-distance driving and prolonged heightened cognitive loads could be factors for allostasis and the gradual development of disease or illness among transportation workers.

A PPG signal is an alternative to the ECG signal to monitor and collect information from the cardiovascular system. A PPG signal is more commonly used in affective computing and stress research due to its ease of access and set-up. Together with EDA, the PPG signal could also be used as the primary indicator of cardiovascular activity in many commercialized wearable devices, such as E4 Empatica, Fitbit, Garmin Vivosmart, Shimmer, and Apple Watch.

Office workers experience prolonged heightened cognitive loads similar to transportation workers but are primarily sedentary during work hours. Similar to the work by Smets et al. [68], Van Kraaij et al. [73] studied the effect of chronic workplace stress among office workers using PPG-based heart rate from a wearable device. In addition, Van Kraaij's team suggested that gender and circadian rhythm modulate stress among office workers. In contrast, Gjoreski et al. [52] on students uses data derived from a PPG signal to assess chronic stress in constrained and unconstrained environments. Similarly, Coutt's team [46] used PPG-based data to detect symptoms of stress among students.

The PPG signal is also widely used in chronic workplace stress studies among healthcare workers. For example, according to a study by Feng et al. [50], nurses who work the night shift are more sedentary than day shift nurses, according to PPG-based heart rate data. A sedentary lifestyle compounded with chronic stress has increased the likelihood of weight gain and cardiovascular diseases. Likewise, chronic workplace stress among attending surgeons and general surgery residents leads to poor medical judgment. Medical errors result in adverse clinical events in patients and severely affect their quality of life. The study by Hirten et al. [18] found that heart rate variability (HRV) calculated from PPG data could detect and monitor chronic stress among surgical staff. Changes in HRV could be used as indicators of chronic stress on surgical staff and help minimize medical errors.

Similarly, Kaczor et al. [61] used PPG-based heart rate and EDA data to study chronic stress among emergency medicine physicians. Kaczor's team suggests a time delay between the manifestation of mounted stress response and when a stressful event is recognized. In addition, their findings support prolonged experimental protocols and data collection to accurately study allostasis due to chronic stress. In a study by Burghardt et al. [16], they examined the effects of life events on a sizeable population of healthcare workers. Burghardt's team analyzed PPG-based heart rate data and contextual data to predict positive and negative emotions correlated with stress and anxiety levels due to significant life events (i.e., death in the family or job promotion). Due to its long collection duration of relevant data, the work by Burghardt's team could be used to build an allostatic load model and measure the likelihood of a worker developing diseases due to chronic stress.

Chronic workplace stress among healthcare workers has worsened throughout the COVID-19 pandemic, with many reporting extreme physical fatigue and mental health issues. A study by Hosseini et al. [54] on frontline nurses against the COVID-19 pandemic provided a new dataset, including PPG and EDA signals, to study the effects of chronic stress on healthcare workers. Similarly, Zhuo et al. [76] used data from a PPG signal to explore the relationship between chronic stress and sleep patterns among hospital workers in Wuhan, China, during the early days of the pandemic. In addition, Hirten et al. [18] used PPG signal data to measure HRV and study stress resilience among healthcare workers during the COVID-19 pandemic. Hirten's team found that healthcare workers are more resilient against stress than the general population and have distinct stress profiles. At the time of writing, an ongoing clinical trial by Clingan et al. [17] also aims to use PPG data, among other sensors, to examine the impact of pandemic-related stress and anxiety and their correlation with COVID-19 infections among healthcare workers.

3.1.3 Psychological Data

The allostatic load model's psychologic component is vital in mounting a stress response. Since the psychologic system is cascaded with the physiologic system, perception of challenges or threats and innate or natural responses determines the physiological reaction of the autonomic nervous system. Psychological data, such as behavioural patterns and contextual data, could augment physiological signal features to evaluate the effects of chronic stress consistent with the allostatic load model. Popular self-report questionnaires, such as the Positive Affect and Negative Affect Schedule (PANAS) [50], Perceived Stress Scale (PSS) [51] [18] [55] [69] [72] [68] [73] [46], Stress Trait Anxiety Inventory (STAI) [50] [52] [46], and Depression Anxiety Stress Scales (DASS) [42] [46], provide psychometric measures of affect, mood, and distress experienced by a person. The DASS questionnaire, in particular, could be instrumental in assessing the effects of chronic stress among workers. Typically documented through diaries, interviews, questionnaires, behavioural patterns, and contextual data could be correlated with physiological data from wearable sensors. However, completing questionnaires during a stress study in the workplace could hinder a worker's on-the-job performance and introduce an unintended stress source. Therefore, we could use wearable sensors to collect behavioural patterns and contextual data and correlate them with physiological data. A collection of works by Kusserow et al. [84] shows that behavioural patterns and contextual data are essential factors to consider in studying stress since the experience and perception of stress are person-specific. Locations, movement, and posture data could also aid in inferring environmental and psychosocial factors contributing to allostasis.

A study by Mozgovoy [64] proposed the use of physical activity levels using accelerometer data to complement both PPG-based heart rate and EDA signals to improve stress detection in office workers. Mozgovoy found high cognitive load levels but low physical activity levels among office workers. Mozgovoy's finding suggests that behavioural patterns could be used as indicators of chronic stress and enhance stress detection from physiological stress biomarkers. A similar work by Sun et al. [70] on students showed the importance of pairing accelerometer data with ECG and EDA signals by improving stress classification accuracy. Mozgovoy's and Sun's conclusions are supported by independent studies by Booth et al. [41] and Yang et al. [44] on office workers. In addition to suggesting that stress detection and prediction in dynamic settings are multimodal, Booth's team encourages including contextual information such as environmental and mobile phone activity to explain physiological data observed from wearable devices. Interestingly, Yang's team found that office workers engaged in mentally taxing activities tend to display more significant changes in their postures than in relaxed states. Yang's

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team suggested that coping strategies, such as body posture changes or leg movements, could be used to infer stress among office workers in addition to EDA data.

Interactions with computer peripherals among office workers could also reflect behavioural patterns associated with stress. A study by Silva et al. [85] found that some combinations of keystrokes, key pressures, mouse movements, and click pressures could be used to indicate stress among office workers. Silva's team's findings are complemented by the work of Banholzer et al. [86], which suggested a trade-off between accuracy and speed in mouse movements during stressful tasks. Specifically, Banholzer's team found that persons under stress move their mice rapidly and inaccurately or slowly but accurately. Furthermore, Hernandez et al. [87] found that computer users under stress tend to apply more significant pressure to their keystrokes and grip their mice tighter. Hernandez's team adds that pressures applied on computer peripherals during stressful situations are task- and person-specific. Tendencies of carpal tunnel or rheumatoid arthritis among office workers due to chronic workplace stress could be a potential avenue for an allostatic study. Although studies on peripheral device interactions have helped detect stress from office workers, their associations with psychological and physiological mechanisms contributing to allostasis are yet to be explored.

Posture, movements, and demeanour could also indicate allostatic development among construction workers. Risky and aggressive behaviours as a response to stress are embedded within the allostatic load model. Risky and aggressive behaviours put workers at risk of injury, especially at construction sites. A study by Zhao et al. [88] suggested that improper body postures due to chronic awkward work postures could lead to musculoskeletal diseases among construction workers. A similar study by Choi et al. [45] used video data correlated with EDA to monitor perceptions of high-risk activities among construction workers, such as ladder climbing or power tools. Choi's team suggested that high-risk activities could be indicated from EDA signal features and validated with video data. The work by Paredes et al. [89] shows that stress during driving could be inferred from a driver's interaction with a steering wheel. Paredes' team suggested that angular or rotational movements from a steering wheel could be correlated with the activity of the arm muscles during stressful driving. Recognition and discouraging risk-taking behaviours and non-ergonomic situations could minimize the likelihood of potentially life-altering injuries or musculoskeletal disorders.

Healthcare workers experience chronic heightened cognitive loads and mental health issues, combined with extreme physical fatigue, which makes them vulnerable to diseases and illnesses. In addition to the ECG signal, Gaballah et al. [51] showed that stress detection among healthcare workers could be significantly improved using a subject's location and speech signal features. Gaballah's team showed that a subject's environment could affect their perception of stress as reflected in their circadian rhythm and changes in pitch, tone, and frequencies of their speech signals. Burghardt et al.'s study [16] on healthcare workers used psychological constructs to measure stress, anxiety, and positive and negative affect. Information from Burghardt's team's psychological constructs was used to align with PPG-based heart rate data and improve the classification of atypical events in the workplace. Night shift nurses tend to be more sedentary than day shift nurses, as suggested by the findings of Feng et al.'s study [50], similar to Mozgovoy's study [64]. Combining behavioural and physiological data also found that night shift nurses have poorer sleep quality, misaligned circadian rhythm, and overall lower life satisfaction than day shift nurses. Over long periods, increasing allostatic load and poor physiological and psychological health put night shift nurses at a higher risk of developing diseases and illnesses than their day shift counterparts. Feng et al.'s findings are supported by the study by Zhuo et al. [76], which explores the effect of worsened chronic workplace stress for healthcare workers due to the COVID-19 pandemic. Zhuo's team suggested that overactivity of the HPA axis among frontline workers contributed to increased insomnia and obstructive sleep apnea incidences. Furthermore, Zhuo's team suggested that psychological distress could significantly impact sleep quality and duration.

Lastly, environmental data within the workplace could be used to assess potential hazards to worker health and safety. In addition to chronic workplace stress, chronic exposure to pollution, toxic fumes, and excessive heat could contribute to increased allostasis and the development of diseases and illnesses. Wu et al. [74] designed a wearable sensor network that monitors ambient temperature, humidity, ultraviolet light exposure, and carbon dioxide concentration in addition to body temperature and heart rate. Similarly, Fazio et al. [48] developed a self-powered garment, harnessing mechanical, thermal, solar, and radiofrequency energies to power PPG sensors, accelerometers, and toxic particulate sensors, such as carbon monoxide and sulfur dioxide sensors. Environmental data provides additional context to worker health and safety, especially at work sites with harsh environments.

3.2 Physiological Signal Features as Equivalents of Traditional Stress Biomarkers

Physiological signal features could represent traditional stress biomarkers to measure allostatic load due to chronic workplace stress. Specifically, physiological signal features from ECG, PPG, and EDA signals could be used as proxies for traditional stress biomarkers, which are otherwise challenging to collect and monitor in a workplace environment. In addition, physiological signal features may help explain workers' behavioral patterns under chronic stress and provide a holistic allostatic load model. In the following sections, we present commonly extracted physiological signal features that could serve as equivalents of traditional stress biomarkers from the cardiovascular, metabolic, and neuroendocrine systems.

3.2.1 Signal Feature Equivalents of Cardiovascular Stress Biomarkers

Heart rate (HR) is the most common stress biomarker. HR is calculated using the number of heartbeats within a specified period. The peaks of either a PPG signal or the R-wave of an ECG signal could signify heartbeats. An increase in HR could indicate a heightened autonomic response toward stress. In contrast, a decreased or sustained HR could indicate an under-reaction towards stress or a lack of an appropriate response. Although less frequently used in allostatic load studies, [7] [34] [35] [36], heart rate and other features of an inter-beat interval (IBI) time-series have been used as indicators of stress [13] [16] [15] [17] [48] [53] [41] [64] [51] [54] [61] [50].

Heart rate variability (HRV) is one of the features of an IBI time series that reflects changes in cardiac activity as the body adjusts to perceived threats or challenges. When the body fails to adapt to chronic stress, HRV could decrease and may indicate an increase in allostatic load. Moreover, decreased HRV is a precursor to cardiac arrhythmias [90], [91] due to chronic stress. HRV has time and frequency domain and non-linear features, which could be used to assess the stress response of the different branches of the autonomic nervous system, including the HPA and SAM axes. Below, we review some of the frequently used time and frequency domain and non-linear features of HRV for stress detection in the workplace. While we included studies that do not focus on workers, they have potential implications for evaluating allostatic load due to chronic workplace stress. The work by Shaffer and Ginsberg provides a comprehensive list of HRV metrics and data collection practices to ensure data fidelity [91].

Time-domain HRV metrics are based on the time variations between consecutive heartbeats. The standard deviation of successive differences between normal-to-normal beats (SDNN) and its root mean squared (RMSSD) are the two most common time-domain HRV metrics. While SDNN is the primary measure for cardiac risk, RMSSD provides an estimate of changes in vagal activation [91]. In recent studies using off-the-shelf wearables, SDNN and RMSSD have been used to correlate acute and chronic workplace stress experienced by trauma surgeons [62], by workers in harsh environments [13], first responders and tactical operators [24], office workers [41] [39], and by healthcare workers during the COVID-19 pandemic [18]. Low SDNN values ($\leq$50 ms) due to chronic workplace stress have been classified as an unhealthy range [91] and may indicate an increased likelihood of developing cardiovascular diseases.

Frequency-domain HRV metrics are calculated from frequency spectrum bands of an IBI time series using Fast Fourier Transform (FFT) [90], [91]. Frequency band ranges of the HRV spectrum are categorized as ultra-low (ULF, $\leq$ 0.003 Hz), very-low (VLF, 0.003 - 0.04 Hz), low (LF, 0.04 Hz - 0.15 Hz) and high (HF, 0.15 Hz - 0.40 Hz) frequency bands. Power density under each band signifies specific autonomic functions such as metabolism, respiration, blood pressure, and temperature regulation.

While the power density under the VLF band is one of the relevant HRV features for stress detection [47] [42] [68] [46], low power density values of LF and HF bands directly correlate with autonomic dysregulation leading to symaptho-vagal imbalance. A sympatho-vagal imbalance was previously associated with psychological stress and psychiatric disorders such as post-traumatic stress disorder (PTSD) caused by combat exposure [92] and drowsiness from general stress, fatigue, or substance influence [40]. The ratio between the power densities of the LF and HF band provides a measure of activation balance between the sympathetic and parasympathetic nervous systems (SNS and PNS) to ascertain the flexibility of the autonomic nervous system to mount a stress response [24], [40], [92]. Autonomic imbalance and rigidity could cause delayed or inadequate response against chronic stress. As per the allostatic load model, a delayed or inadequate response against stress causes aggression, frustration, and anxiety. Negative affect caused by delayed or inadequate response against stress leads to a prolonged heightened physiological state resulting in allostasis.

Finally, non-linear metrics of HRV provide measures of the unpredictability of an IBI time series which are challenging to acquire from time and frequency domain techniques. Among the non-linear HRV metrics, the Poincaré plot and its features are commonly used in stress studies. A Poincaré plot illustrates a two-dimensional map of time-variation patterns between successive IBIs [91]. For example, an ellipse could be fitted onto a Poincaré plot, and non-linear features could be calculated, such as its length (SD2), width (SD1), and area (S). Features of the Poincaré plot have been used to assess autonomic dysregulation in schizophrenic patients from a study by Liu et al. [93] and a review of stress research on first responders by Corrigan et al. [24]. Both teams independently observed an overall decrease in SD1 and SD2 values during a stress response, indicating dysregulated activation of the SNS and PNS. Dysfunctional activation of the SNS and PNS due to chronic stress or negative affect have been documented as precursors to cardiac arrhythmias [94] [32], increased allostatic load, and decreased quality of life.

3.2.2 Signal Feature Equivalents of Metabolic and Neuroendocrine Stress Biomarkers

EDA features could represent physiological equivalents of metabolic and neuroendocrine stress biomarkers. As previously discussed, dysfunction of the SNS and PNS could develop due to chronic workplace stress. EDA could indicate dysfunctions of the SNS due to metabolic diseases, such as diabetes, or neuroendocrine dysregulation due to heightened and prolonged cognitive loads or mental health issues. Choi et al. [45] demonstrated the feasibility of using EDA features to detect stress due to perceived levels of risk among construction workers.

EDA could be separated into two components: skin conductance level (SCL) and skin conductance response (SCR), both measured in microsiemens (μS) [80], [82]. SCL is the tonic component of an EDA signal or the continuous background activity of the SNS. On the other hand, SCR is the phasic component of an EDA signal and could be elicited with specific external stressors. SCRs directly convey the changes in skin conductance due to activation of the SNS and are valuable for stress studies. SCLs and SCRs could be separated from each other via de-trending methods such as peak-picking-algorithm [95] and regularization via least-squares [96]. A convex optimization approach (cvxEDA) by Greco et al. [97] effectively separates the tonic and phasic components of EDA and is widely used in EDA studies. Because of SCRs' close association with external stimulation, SCRs, and their features are used primarily for stress studies. Similar to an IBI time series, features from EDA's SCRs could be extracted using time- and frequency- and time-frequency-domain methods. Shukla et al. published a

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comprehensive list of all SCR features that could be used for affective computing [98] and may provide good indicators of SNS activity and disease prediction.

Time domain features, such as latency, rise time, 50% and 63% amplitude recovery time, amplitude, response duration, and area under the response curve [80], [82] of the EDA signal, have been used to study workplace stress [43], [45], [99]. Some of the above features have been used by Healey et al. [43] to detect and quantify orienting responses [82], also known as SCRs, from truck drivers as they drove through city roads and motorways. Changes in the morphology of an orienting response could be used to assess the SNS' activity under stress. A study by Smets et al. [68] found that SCRs from stressed individuals have increased signal power indicating changes in EDA signal morphology. Likewise, studies by Umematsu et al. [71] [72] provided evidence of the potential use of EDA's time domain features to predict stress and affect among office workers and students. Umematsu et al.'s work could translate to predicting metabolic and neuroendocrine diseases due to chronic workplace stress.

As Shukla et al. cited in their work, studies that use frequency domain features of EDA are limited [98]. A study by Posada-Quintero et al. [100] attempted to translate the power spectral analysis methods for an HRV time series, dividing the EDA spectrum into similar frequency bands. Although Posada-Quintero et al. observed a correlation between specific EDA and HRV spectral bands during stress, further studies are needed to establish physiological associations of the SNS activation to the different ranges of EDA frequency bands, similar to the HRV frequency bands detailed in previous works [90], [91].

Due to the non-stationary and time-varying nature of EDA, time-frequency analysis methods are useful for extracting features from SCRs relevant to a stress response. Time-frequency analysis methods such as short-time Fourier transform (STFT), Hilbert-Huang transform (HHT) [101] and wavelet transform [102] could provide information on temporal changes in spectral properties of a signal. For example, the work by Ganapathy et al. [103] demonstrated a two-dimensional spectral map of an EDA obtained using STFT. A time-frequency map of an EDA could help determine changes in spectral properties of orienting responses due to chronic workplace stress. Similarly, Ileri et al. [57] used HHT and STFT to detect physical, cognitive, and emotional stress from subjects involved in Birjandtalab et al.'s study [58]. Ileri's team suggests that EDA features derived from HHT and STFT could be better used for detecting cognitive stress. Although Ileri's team used data from students, their finding is supported by previous studies that used features of EDA from healthcare [61] [54], construction [45] and office workers [71] [72]. Increased and prolonged cognitive stress has been shown to translate to adverse health effects among healthcare [16] [76] [51] and office workers [71] [64] due to the cascading effect of the psychologic system to many physiologic systems.

Wavelet transform has also been used for workplace stress detection in affective computing, albeit sparsely. While the works by Lee et al. [63] and Shukla et al. [67] used EDA features to detect stress among students and workers, they used wavelets only for artifact removal and signal denoising. Nonetheless, Chen et al. [14] showed that wavelet features of EDA, combined with other stress biomarkers, could provide good accuracy for stress detection among truck drivers from Healey et al.'s study [43]. Variations of wavelet transform for EDA have also been used in emotion detection, although not from workers exposed to chronic stress. Feng et al. [49] aimed to distinguish emotions from children using EDA features from continuous wavelet transform (CWT). Moreover, EDA features from discrete wavelet transform (DWT) have been demonstrated to reflect dysregulation of the SNS and PNS due to stressors that could result in social anxiety disorders, as shown previously by Sharma et al. [104]. Expanding usage of time-frequency feature extraction methods for EDA could be beneficial in incorporating concepts of allostasis in affective computing. Temporal analysis of spectral changes of stress biomarkers could provide tools to monitor the increase in allostatic load due to chronic stress. Moreover, regular evaluation of allostatic load could be used to predict metabolic or neuroendocrine diseases due to chronic stress effectively.

3.2.3 Potential Equivalents of Stress Biomarkers from Physiological and Psychological Data Features for Allostatic Load Measurement

Previous sections of our survey hinted at using various combinations of ECG, PPG, and EDA to study the effects of chronic workplace stress. We also reviewed studies that combined physiological equivalents of stress biomarkers with behavioural patterns or contextual information to assess the effects of stress on worker well-being and performance in the workplace. In addition to ECG, PPG, and EDA signals, respiratory inductance plethysmograph (RIP), skin temperature (ST), and accelerometer (ACC) data are typically used to evaluate the effects of chronic workplace stress. RIP, ST, and ACC signal features could indicate autonomic activity due to stress; however, they are not classified as traditional stress biomarkers under the allostatic load model. Nonetheless, RIP, ST, and ACC features could enhance stress studies analysis and are worth noting.

The sensor networks by Healey et al. [43], Ertin et al. [56], Aqueveque et al. [13] and Fazio et al. [48] included sensors for RIP, ST, and ACC to augment detection and classification of stressed individuals. A study by Smith et al. [69] specifically used RIP as a form of biofeedback and mindfulness training to regulate the respiration of workers during stressful events. Smith's team found that conscious regulation of respiration reduces distress and anxiety and improves overall well-being in the workplace. RIP was also correlated with changes in the high-frequency bands (0.15 Hz - 0.40 Hz) of an HRV spectrum [91]. A study by Mozgovoy demonstrated that motion intensity from ACC data could be used to detect stress in place of physiological signals [64]. Furthermore, ACC features could be used to estimate energy expenditure for different activities [105]. Skin temperature is usually correlated with EDA due to the autonomic control of thermoregulation. Studies by Umematsu et al. [71] [72] used ST and ACC to weigh EDA features and to correct for artifacts that would otherwise affect the prediction and classification of stress among office workers and students. In addition, ST and metabolism, approximated from ACC channel data [91], were also correlated with changes in the ultra-low frequency bands ($\leq$ 0.003 Hz) of an HRV spectrum.

Lastly, features from electromyographs (EMG) [14] [15] [47] [43] [99] and electroencephalographs (EEG) [59] [60] are also used in stress research, however infrequently. For example, EEG features could be directly correlated with psychological responses, and EMG signals from the contraction of the upper back and neck muscles have been associated with stress. However, EMG and EEG sensing require different host materials (i.e., a helmet or cap) or sensing devices and setups, which may hinder other workplaces that do not require specific personal protective equipment.

3.3 Machine Learning Methods for Allostatic Load Model Development

Machine learning is a sub-field of computer science that uses algorithms to mimic the human brain's pattern learning or training process to classify new information or predict future states or actions [106]. Similar to an allostatic load model, using combinations of physiological and psychological features as inputs for machine learning methods could be used to assess the likelihood of developing diseases and illnesses among workers. The studies we included in this review used a variety of standard machine learning methods to distinguish individuals and groups of workers under stress, such as random forest (RF) [16] [52] [54] [66] [68] [71], decision tree (DT) [16] [61] [70] [103], support vector machines (SVM) [16] [65] [55] [103] [57] [60] [14] [40] [47] [52] [70], k-nearest neighbour (k-NN) [47] [57] [63] [52], linear discriminant analysis (LDA) [103] [61], Adaboost [16] [65], logistic regression [16] [63] [61], multilayer perceptrons(MLP) [16] [103] [57] [41] [47], and statistical models, such as Gaussian mixed models (GMM) [58] [64] and hidden markov models (HMM) [65] [16]. While the nature of machine learning techniques is beyond the scope of our survey, we present below some of the notable uses of machine learning algorithms for assessing chronic workplace stress.

Booth et al. [41], Umematsu et al. [71], and Smets et al. [68] used standard machine learning methods to detect stress among office workers. Among the other methods Booth's team used, they reported using multimodal data with RF provides excellent classification performance for 82% of its study participants. Similarly, the work by Umematsu et al. showed that office workers' moods, stress levels, and physical health could be predicted using RF with low absolute errors. Furthermore, Umematsu's team identified features important for predicting stress and health (raw skin temperature) and mood (step count). Interestingly, the work by Umematsu's team alludes to an allostatic load model of stress since they used physiological and behavioural data to predict a subject's health for the next workday. The work by Smets' team showed that an RF-based stress classification model could achieve an F1-score of 0.43 using data acquired from office workers.

Studies for detecting chronic workplace stress among transportation staff have also benefited from some standard machine learning methods. Using data from Healey et al.'s [43] earlier experiments, Dalmeida et al. [47], Chen et al. [14], and Shukla et al. [98] have used a variety of machine learning methods to detect stress in truck drivers. For example, Dalmeida et al. showed that MLP performs best for classifying stressed individuals using HRV features compared to SVM and RF, with 80% recall and 72% F1 score. On the other hand, Chen's team showed that SVM provided the best performance using all multimodal features available (EDA, ECG, and RIP) with 99% precision but required significant computational resources. However, when multimodal features are reduced in dimension, they still achieve a respectable 89% precision using an SVM with a radial basis function (RBF) kernel. Similarly, Shukla's team used an SVM with an RBF kernel to classify emotional arousal among transportation staff using EDA features. While Shukla's team reported an average F1 score of 61% from an SVM classifier across all participants, participant-specific SVM models yielded better accuracy (84% vs. 61%).

Stress classification among healthcare workers using standard machine learning techniques was previously performed by Burghardt et al. [16], Kaczor et al. [61], and Hosseini et al. [54]. Burghardt's team and Hosseini's team used RF to classify stressed healthcare workers. While Hosseini's team did not report the usual performance metrics for classification, they showed that their EDA features increased in entropy to indicate that EDA features could be better predictors of stress. On the other hand, Burghardt's team reported that RF is better for modeling positive atypical events among healthcare workers with a maximum F1 score of 37% and precision of 32%. Burghardt's team attributed the low F1 scores and precision to the small number of atypical events reported by their subjects. Lastly, Kaczor's team used three methods for pairwise classification of baseline, pre-stress, and post-stress events among emergency physicians. Kaczor's team found that a bagged trees model performed the best (69% accuracy) when comparing baseline and pre-stress conditions. Kaczor's team's findings reinforce their finding that a stress response could be mounted before it could be recognized.

Some standard machine learning methods were used as foundations to create intricate prediction frameworks beyond their initial classification aims. Although the following models were not made specifically for workers under chronic stress, prediction is essential for allostatic load models of stress. Measuring the likelihood of diseases and illnesses due to gradually increasing allostatic load could be an essential tool for proactive mitigation of the adverse health effects of chronic stress. A stress prediction model developed by Plarre et al. [65] used physiological signal features and behavioural patterns to infer stress from wearable devices continuously. They created an SVM-based physiological classifier cascaded with an HMM to predict a subject's perceived stress, assuming it lingers long after a physiological response. Plarre's team reported remarkable correlations (r = 0.71) between self-reported stress levels by participants and predicted stress levels by their model.

Similarly, Hovsepian et al. [55] developed a model to continuously assess the likelihood of stress using data from wearable devices (cStress) and self-reported stress as references. cStress is based on an SVM classifier with an RBF kernel and a Bayesian network to infer stress continuously. Although cStress does not offer to predict the likelihood of disease, Hovsepian's team demonstrated that cStress could classify stress individuals and provide a probability of stress with a median F1 value of 71% and a median accuracy of 72%. Plarre et al. and Hovsepian et al. show that combinations of standard machine learning methods could be practical tools for classifying and predicting the likelihood of stress. Moreover, machine learning models that could predict stressed states could be potentially used to predict allostatic load indices due to chronic workplace stress.

Advanced machine learning methods such as convolutional and recurrent neural networks (CNN and RNN) and their combinations have also been used for stress classification and prediction. CNN architectures incorporate data matrix convolution with traditional neural network elements to handle classification or prediction for large amounts of multidimensional data, such as video or image streams [107]. For example, Cho et al. [15] used raw ECG signals as inputs to an 8-layer CNN architecture to detect stress among truck drivers. Cho's team proposed a CNN for stress detection to bypass preprocessing and feature extraction steps (i.e., HRV) usually performed in traditional classification frameworks. Cho's study demonstrates improved stress detection accuracy, at approximately 90%, compared to standard machine learning methods, with a maximum 53% accuracy using RF.

Similarly, Jebelli et al. [59] created a 4-layer CNN architecture to detect stress among construction workers using raw EEG signals, with salivary cortisol as the gold standard for stress levels. Although they reported a lower accuracy score (64%) than Cho's team's ECG and 8-layer architecture, Jebelli's team showed that CNN could be used for stress detection among construction workers using EEG data. However, EEGs may not be suitable for general stress detection since EEGs measure the activity of the central nervous system. In contrast, peripheral nervous system activities directly associated with a stress response could be better sensed with ECG, PPG, or EDA signals.

On the other hand, RNN architectures adopt closed-loop connections within the hidden layers of their neural network to store and process previous input signals over long periods. The structure of RNNs enables prediction of the following signal segment or time series sequence [108]; hence, RNN architectures are promising machine learning methods to build allostatic load models, especially for chronic workplace stress. Since increased allostatic loads due to workplace stress could be better observed from chronic stress exposure, data must be collected over long periods and assessed using time-aware methods. Therefore, the likelihood of diseases and illnesses due to chronic workplace stress could be better assessed with RNN architectures. Among numerous RNN architectures, long short-term memory (LSTM) has demonstrated its efficiency in learning long-range dependencies and robustness against vanishing or exploding learning gradients. For example, Booth et al. [41] used LSTM on multimodal data to study the effects of stress among office workers. While they reported worse performance for stress classification by LSTM than RF, Booth's team acknowledged that their study lacked sufficient time series data to fully take advantage of LSTM's capabilities. In contrast, the study by Coutts et al. [46] showed that satisfactory classification performance could be achieved with LSTM using datasets collected only in short periods, reporting as much as 76% stress classification accuracy.

In contrast, Umematsu et al. [72] showed that using multimodal data as inputs to a 3-layer LSTM, stress levels, health, and mood could be predicted among students. Umematsu's team reported that their LSTM architecture is 84%, 90%, and 84% accurate in predicting next-day stress levels, health, and mood, respectively. Moreover, Umematsu's team showed that physiological data from wearable sensors collected during the day is sufficient for well-being prediction. While Umematsu's study used student data, it has significant implications for building an allostatic load model for predicting stress levels, mood, and health among workers under chronic stress.

A bidirectional LSTM (bi-LSTM), a variation of LSTM, was used by Gaballah et al. [51] to detect stress among healthcare workers using both physiological and psychological data. Using past and future data for stress detection, Gaballah's team reported that a 2-layer bi-LSTM provides approximately 65% accuracy and 63% F1 score by combining audio, location, and physiological. The results from Gaballah et al.'s study reinforce the need for behavioural patterns and contextual information in combination with physiological data to accurately evaluate the effects of allostasis due to chronic stress.

Finally, some stress studies have implemented combinations of CNN and RNN architectures to leverage the unique advantages of either CNN or RNN. For example, Zhao et al.'s work [88] combined a layer of CNN and a 2-layer LSTM to detect chronic non-ergonomic postures among construction workers using data from inertial measurement units (IMU). Chronic non-ergonomic postures could lead to musculoskeletal diseases which impede a worker's on-the-job performance. Zhao's team reported that a layer of CNN marginally improves a 2-layer LSTM's ability to detect non-ergonomic postures by 2%, with an overall F1 score of 85%. However, Zhao's team also found that increasing CNN layers decreased the performance of their learning architecture which they attributed to overfitting.

4 Discussion

We emphasize the need and relevance of incorporating the allostatic load model in affective computing to help create a holistic model for predicting potential diseases and illnesses that may emerge due to stress. Models for detection and prediction could be used to proactively mitigate the adverse long-term health effects of stress and ensure worker well-being. We surveyed notable studies on acute and chronic stress within the field of affective computing that could benefit from an allostatic load model of stress. We reviewed works focused on dynamic environments, such as the workplace, using traditional elements of stress research such as wearable devices, signal or data feature extraction, and machine learning methods. Confounding factors and challenges in ambulatory stress research have been discussed at length in a previous work [39]. We included works that may not have been performed with workers or in a workplace but could significantly affect worker well-being. Furthermore, we included works that could benefit from incorporating an allostatic load model of stress using traditional stress study elements in affective computing.

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Current chronic stress research practices in affective computing could be adapted to the allostatic load model by accounting for the following factors. 1) data features must have a physiological and psychological basis in the autonomic nature of stress beyond their apparent statistical significance; 2) aside from being used as data labels, behavioural data, and contextual information could be used to explain trends in physiological data and improve detection of allostasis; 3) due to the gradual and cumulative nature of allostasis, data collection periods must be significantly increased to provide sufficient data for disease prediction; and 4) hyperparameters of an allostatic load model of stress based on machine learning methods could be tuned to the unique stress response of an individual and, in turn, assess their risk for diseases and illnesses due to chronic stress.

Calculating a clinical allostatic load index relies on various stress biomarkers, such as salivary cortisol, urinary adrenaline, immunological proteins, or metabolic activity. However, access is limited to the majority of traditional stress biomarkers in affective computing. Therefore, we seek physiological and psychological equivalents of traditional stress biomarkers to directly or indirectly assess the activity of the autonomic nervous system due to chronic stress. Signal features that have established physiological correlate to stress, such as an ECG, PPG, or EDA, could be used as physiological equivalents of stress biomarkers. ECG, PPG, and EDA are also accessible in a dynamic environment through wearable sensors, either custom-made or off-the-shelf. Just as traditional stress biomarkers for allostatic load index calculation have been clinically validated, signal and data features extracted for stress detection and prediction must have physiological significance beyond reported statistics. Some of the temporal and spectral features of ECG, PPG, and EDA have been established to be physiologically relevant to stress [90] [91] [80] [82]. However, some features used in several studies may not have clinical significance to stress. While including non-clinical features may aid in stress classification, it could hamper predicting stress-related diseases and illnesses. Once the relevance of signal features to stress is established, an allostatic load index could be calculated from the equivalents of traditional stress biomarkers. For example, select ECG, PPG, and EDA signal features could be weighed based on their interactions with the autonomic nervous system and activity levels due to chronic workplace stress. Weighted data features could be summed up to a score or fitted onto a curve to determine the risks of developing diseases and illnesses.

Behavioural patterns and contextual information, such as psychological profiles or psychosocial states, could help explain changes in physiological stress biomarkers that may indicate an increase in allostatic load [38] [36] [35]. Therefore, behavioural data and contextual information are essential to assess stress' negative health effects accurately. Negative employee behaviour patterns, such as absenteeism, risk-taking behaviour, and burnout, could indicate underlying severe medical or mental health issues due to chronic workplace stress. For example, observations made by Lampert et al. [94] on individuals who suffered episodes of a cardiac arrhythmia, catecholaminergic polymorphic ventricular tachycardia (CPVT) [109], was predicated by intense feelings of anger. Despite the established relationship between physiological and psychological systems [1] [25] [7], the contributions of behavioural data and contextual information to the stress response are under-recognized in affective computing, especially in the workplace. Previous studies have shown the benefits of including behavioural data for enhancing stress classification and prediction tasks [65] [55] [66], which is consistent with the allostatic load model. However, the technical literature is sparse on emotion and affect recognition using psychological or psychometric features that could be an autonomic stress response. Our previous work attempted to introduce new psychometric features to improve stress detection using data from wearables. Our results suggest that psychometric features could improve the classification of acutely stressed individuals [110]. In addition to using psychological data as labels to categorize data for classification or regression, psychological data could be treated as indicators or predictors of a stress response in affective computing.

However, psychological data need to be explicitly expressed by a subject. Unlike wearable devices that could passively collect data, the mere act of psychological data collection could hamper study protocols and become an unintended stressor. Moreover, psychological data is challenging to replicate and validate due to its inherent subjectivity. Hence the reasonable hesitance of groups to incorporate this data type into their studies. Behavioural data, however, could be inferred from wearable device data. For example, movement or changes in posture could assess physical activity associated with a physiological stress response. In addition, contextual information, such as locations, light exposure, or ambient temperature, could also aid in explaining an individual's stress response concerning their exposure to specific environmental factors.

Neuroscience, psychology, and psychiatry stress studies are performed over long periods, including patient follow-ups and clinical work updates. From the first observations made by Selye on rats exposed to non-specific stressors [111] [112]; to the study by Sterling and Eyer [26] on cohorts of peoples after major catastrophic events; and the present stress studies [23], the adverse health effects of stress could be adequately evaluated using data collected over long periods. Supported by previous studies [73] [71] [41], measuring allostatic load from workers may benefit from data collected over multiple shifts and workdays instead of only a couple of hours or less. A study by Gillespie et al. [3] is an excellent example of a stress study, as it follows a cohort of people over ten years to create connections between depression, allostatic load, and incidence of heart disease. Gillespie's team found that individuals with increased allostatic load exhibited worse symptoms of depression and increased risk of heart disease, especially among females. Another great example, in the context of chronic workplace stress, is a study by Hulsegge et al. [4], which examined a 5-year data set to elucidate the relationships between shift work, obesity, and the development of diabetes. Hulsegge's team found that shift workers tend to become more obese and suffer from diabetes than non-shift workers. Hulsegge's team attributes their findings to low physical activity, poor sleep quality, and poor diet. Prediction of metabolic and heart diseases may not provide accurate results when stress data is limited. Among the studies we reviewed, the works by Burghardt et al. [16], Clingan et al. [17], Hirten et al. [18], Booth et al. [41], Kaczor et al. [61], and Feng et al. [50] could be considered consistent with the allostatic load model since their analyses on workers' physiological and psychological data include data for more than a working day. The nature of their data collection protocols allows for examining the gradual development of allostatic load due to chronic workplace stress. While data storage and processing power could become issues with large databases, advances in efficient big-data and machine-learning frameworks could help alleviate these concerns [113], [114], [115].

Lastly, an individual's stress response is unique and will depend on their psychological and physiological predispositions, past experiences, and learned coping strategies [84] [87] [70]. Therefore, an allostatic load model could aid in implementing a predictive model tailored to an individual. However, an individual's stress response is often blurred when searching for a generalizable machine-learning model, especially in group classification tasks. RNN architectures, like LSTM and its variants, could accommodate data collected over long periods and could be used to identify and predict psychological and physiological trends. Therefore, RNN architectures could prove valuable for creating personalized prediction models of diseases and illnesses due to chronic workplace stress. Consequently, a collection of RNN architectures could represent a group of individuals for which typical classification algorithms could be implemented without discounting an individual's unique stress response. While personalized stress models could represent the individual, they would require regular patches and hyperparameter re-tuning every so often [116]. Moreover, due to a lack of gold standards in allostatic load measurement and the tendency of an individual to adapt to day-to-day challenges, personalized stress models would be challenging to validate, replicate, and maintain. Nonetheless, models that account for the inherent complexity of a stress response could be instrumental in proactively mitigating the adverse long-term health effects of chronic stress. Predictive stress models could enhance safeguards within the workplace and ensure the impact of diseases and illnesses due to chronic workplace stress is minimized.

5 Summary

Chronic stress poses a risk to a worker's safety and overall well-being. Proactively mitigating chronic stress' adverse long-term health effects could improve a worker's quality of life. Therefore, predictive models that could account for stress's complex and individual nature could be a valuable tool to minimize workplace injuries, absenteeism, and mental health issues. In neuroscience, psychiatry, and psychology, a prolonged heightened physiological and psychological state is known as allostasis. An allostatic load index provides a risk assessment for potential diseases and illnesses due to chronic workplace stress. And lastly, the allostatic load model combines the physiological and behavioural dimensions of stress to evaluate the complex mechanism of a stress response. With the traditional elements of stress studies in affective computing, an allostatic load model of stress may provide measures of the likelihood of diseases and illnesses among workers due to increased allostatic load.

We reviewed notable workplace stress studies within the past decade, including typical stress studies in affective computing (i.e., wearables, signal and data processing, and machine learning methods). We also included studies that are not work-related, but their findings significantly affect overall worker well-being. We discussed how our reviewed works could benefit from incorporating elements of an allostatic load model of stress to predict the likelihood of diseases and illnesses due to chronic workplace stress. We reviewed physiological signals (ECG, PPG, and EDA), behavioural patterns, and contextual information from which data features could be extracted. We also reviewed signal and data features that could serve as physiological equivalents of stress biomarkers used for allostatic load calculations (i.e., HR, HRV, and SCR). Moreover, we reviewed some standard and advanced machine learning methods used to classify and predict workers' stress.

Finally, we recommended adapting an allostatic load model to stress research in affective computing. First, features extracted from physiological signals and psychological data should have clinical relevance to allostasis beyond its apparent statistical importance. Second, behavioural patterns and contextual information could aid in explaining a stress response and improve stress detection and prediction of diseases and illnesses due to increased allostatic load. Third, data collection periods could be significantly extended so that predictions from a model are sufficiently accurate to help proactively mitigate the adverse health effects of increased allostatic load. Lastly, stress models could be tuned to an individual's stress response. They could be beneficial for accurately assessing their risks of diseases and illnesses due to chronic workplace stress. Adapting current chronic stress detection strategies from affective computing to an allostatic load model could enhance worker safety and minimize the effects of adverse long-term health effects of chronic stress.

References

[1] B. S. McEwen, "Physiology and neurobiology of stress and adaptation: central role of the brain," *Physiological reviews*, vol. 87, no. 3, pp. 873–904, 2007.
[2] B. S. McEwen and E. Stellar, "Stress and the individual: Mechanisms leading to disease," *Archives of internal medicine*, vol. 153, no. 18, pp. 2093–2101, 1993.
[3] S. L. Gillespie, C. M. Anderson, S. Zhao, Y. Tan, D. Kline, G. Brock, J. Odei, E. O'Brien, M. Sims, S. A. Lazarus *et al.*, "Allostatic load in the association of depressive symptoms with incident coronary heart disease: The jackson heart study," *Psychoneuroendocrinology*, vol. 109, p. 104369, 2019.
[4] G. Hulsegge, K. I. Proper, B. Loef, H. Paagman, J. R. Anema, and W. van Mechelen, "The mediating role of lifestyle in the relationship between shift work, obesity and diabetes," *International Archives of Occupational and Environmental Health*, pp. 1–9, 2021.
[5] J. Gómez-Salgado, J. Fagundo-Rivera, M. Ortega-Moreno, R. Allande-Cussó, D. Ayuso-Murillo, and C. Ruiz-Frutos, "Night work and breast cancer risk in nurses: Multifactorial risk analysis," *Cancers*, vol. 13, no. 6, p. 1470, 2021.
[6] X. Li, X. Yang, X. Sun, Q. Xue, X. Ma, and J. Liu, "Associations of musculoskeletal disorders with occupational stress and mental health among coal miners in xinjiang, china: a cross-sectional study," *BMC Public Health*, vol. 21, no. 1, pp. 1–10, 2021.

[7] R.-P. Juster, B. S. McEwen, and S. J. Lupien, "Allostatic load biomarkers of chronic stress and impact on health and cognition," *Neuroscience & Biobehavioral Reviews*, vol. 35, no. 1, pp. 2–16, 2010.

[8] M. Sheraton, N. Deo, T. Dutt, S. Surani, D. Hall-Flavin, and R. Kashyap, "Psychological effects of the covid 19 pandemic on healthcare workers globally: A systematic review," *Psychiatry research*, vol. 292, p. 113360, 2020.

[9] A. Sriharan, S. Ratnapalan, A. Tricco, D. Lupea, A. P. Ayala, H. Pang, and D. D. Lee, "Occupational stress, burnout and depression in women in healthcare during covid-19 pandemic: a rapid scoping review," *Frontiers in Global Women's Health*, vol. 1, p. 20, 2020.

[10] P. Lazaro and M. Momayez, "Heat stress in hot underground mines: a brief literature review," *Mining, Metallurgy & Exploration*, vol. 38, no. 1, pp. 497–508, 2021.

[11] N. S. Council. (2021) Injury facts. [Online]. Available: https://injuryfacts.nsc.org/

[12] A. of Worker's Compensation Boards of Canada. (2021) National work injury, disease, and fatality statistics. [Online]. Available: https://awcbc.org/en/statistics/

[13] P. Aqueveque, C. Gutierrez, F. S. Rodríguez, E. J. Pino, A. S. Morales, and E. P. Wiechmann, "Monitoring physiological variables of mining workers at high altitude," *IEEE Transactions on Industry Applications*, vol. 53, no. 3, pp. 2628–2634, 2017.

[14] L.-l. Chen, Y. Zhao, P.-f. Ye, J. Zhang, and J.-z. Zou, "Detecting driving stress in physiological signals based on multimodal feature analysis and kernel classifiers," *Expert Systems with Applications*, vol. 85, pp. 279–291, 2017.

[15] H.-M. Cho, H. Park, S.-Y. Dong, and I. Youn, "Ambulatory and laboratory stress detection based on raw electrocardiogram signals using a convolutional neural network," *Sensors*, vol. 19, no. 20, p. 4408, 2019.

[16] K. Burghardt, N. Tavabi, E. Ferrara, S. Narayanan, and K. Lerman, "Having a bad day? detecting the impact of atypical life events using wearable sensors," *arXiv preprint arXiv:2008.01723*, 2020.

[17] C. A. Clingan, M. Dittakavi, M. Rozwadowski, K. N. Gilley, C. R. Cislo, J. Barabas, E. Sandford, M. Olesnavich, C. Flora, J. Tyler *et al.*, "Monitoring health care workers at risk for covid-19 using wearable sensors and smartphone technology: Protocol for an observational mhealth study," *JMIR research protocols*, vol. 10, no. 5, p. e29562, 2021.

[18] R. P. Hirten, M. Danieletto, L. Tomalin, K. H. Choi, M. Zweig, E. Golden, S. Kaur, D. Helmus, A. Biello, R. Pyzik *et al.*, "Factors associated with longitudinal psychological and physiological stress in health care workers during the covid-19 pandemic: observational study using apple watch data," *Journal of medical Internet research*, vol. 23, no. 9, p. e31295, 2021.

[19] B. A. Hickey, T. Chalmers, P. Newton, C.-T. Lin, D. Sibbritt, C. S. McLachlan, R. Clifton-Bligh, J. Morley, and S. Lal, "Smart devices and wearable technologies to detect and monitor mental health conditions and stress: A systematic review," *Sensors*, vol. 21, no. 10, p. 3461, 2021.

[20] J. Chen, M. Abbod, and J.-S. Shieh, "Pain and stress detection using wearable sensors and devices—a review," *Sensors*, vol. 21, no. 4, p. 1030, 2021.

[21] O. Parlak, "Portable and wearable real-time stress monitoring: A critical review," *Sensors and Actuators Reports*, p. 100036, 2021.

[22] S. Gedam and S. Paul, "A review on mental stress detection using wearable sensors and machine learning techniques," *IEEE Access*, 2021.

[23] J. Guidi, M. Lucente, N. Sonino, and G. A. Fava, "Allostatic load and its impact on health: a systematic review," *Psychotherapy and psychosomatics*, vol. 90, no. 1, pp. 11–27, 2021.

[24] S. L. Corrigan, S. Roberts, S. Warmington, J. Drain, and L. C. Main, "Monitoring stress and allostatic load in first responders and tactical operators using heart rate variability: a systematic review," *BMC public health*, vol. 21, no. 1, pp. 1–16, 2021.

[25] B. S. McEwen and J. C. Wingfield, "The concept of allostasis in biology and biomedicine," *Hormones and behavior*, vol. 43, no. 1, pp. 2–15, 2003.

[26] P. Sterling, "Allostasis: a new paradigm to explain arousal pathology," *Handbook of life stress, cognition and health*, 1988.

[27] B. S. McEwen, "Stress, adaptation, and disease: Allostasis and allostatic load," *Annals of the New York academy of sciences*, vol. 840, no. 1, pp. 33–44, 1998.

[28] M. A. C. Stephens and G. Wand, "Stress and the hpa axi: Role of glucocorticoids in alcohol dependence." *Alcohol research: current reviews*, 2012.

[29] M. J. Garabedian, C. A. Harris, and F. Jeanneteau, "Glucocorticoid receptor action in metabolic and neuronal function," *F1000Research*, vol. 6, 2017.

[30] S. Brady, *Basic neurochemistry: molecular, cellular and medical aspects*. Elsevier, 2005.

[31] S. T. Nyberg, E. I. Fransson, K. Heikkilä, K. Ahola, L. Alfredsson, J. B. Bjorner, M. Borritz, H. Burr, N. Dragano, M. Goldberg *et al.*, "Job strain as a risk factor for type 2 diabetes: a pooled analysis of 124,808 men and women," *Diabetes care*, vol. 37, no. 8, pp. 2268–2275, 2014.

[32] M. Kivimäki and A. Steptoe, "Effects of stress on the development and progression of cardiovascular disease," *Nature Reviews Cardiology*, vol. 15, no. 4, pp. 215–229, 2018.

[33] T. E. Seeman, B. H. Singer, J. W. Rowe, R. I. Horwitz, and B. S. McEwen, "Price of adaptation—allostatic load and its health consequences: Macarthur studies of successful aging," *Archives of internal medicine*, vol. 157, no. 19, pp. 2259–2268, 1997.

[34] D. Mauss, J. Li, B. Schmidt, P. Angerer, and M. N. Jarczok, "Measuring allostatic load in the workforce: a systematic review," *Industrial health*, vol. 53, no. 1, pp. 5–20, 2015.

[35] N. Dich, T. Lange, J. Head, and N. H. Rod, "Work stress, caregiving and allostatic load: Prospective results from whitehall ii cohort study," *Psychosomatic medicine*, vol. 77, no. 5, p. 539, 2015.

[36] R. H. Carlsson, Å. M. Hansen, M. L. Nielsen, M. Blønd, and B. Netterstrøm, "Changes in allostatic load during workplace reorganization," *Journal of Psychosomatic Research*, vol. 103, pp. 34–41, 2017.

[37] P. Kerr, M. B. Da Torre, C.-É. Giguère, S. J. Lupien, and R.-P. Juster, "Occupational gender roles in relation to workplace stress, allostatic load, and mental health of psychiatric hospital workers," *Journal of Psychosomatic Research*, vol. 142, p. 110352, 2021.

[38] D. Mauss, M. N. Jarczok, and J. E. Fischer, "A streamlined approach for assessing the allostatic load index in industrial employees," *Stress*, vol. 18, no. 4, pp. 475–483, 2015.

[39] E. Smets, W. De Raedt, and C. Van Hoof, "Into the wild: the challenges of physiological stress detection in laboratory and ambulatory settings," *IEEE journal of biomedical and health informatics*, vol. 23, no. 2, pp. 463–473, 2018.

[40] M. Awais, N. Badruddin, and M. Drieberg, "A hybrid approach to detect driver drowsiness utilizing physiological signals to improve system performance and wearability," *Sensors*, vol. 17, no. 9, p. 1991, 2017.

[41] B. M. Booth, H. Vrzakova, S. M. Mattingly, G. J. Martinez, L. Faust, and S. K. D'Mello, "Toward robust stress prediction in the age of wearables: Modeling perceived stress in a longitudinal study with information workers," *IEEE Transactions on Affective Computing*, 2022.

[42] T. Chalmers, B. A. Hickey, P. Newton, C.-T. Lin, D. Sibbritt, C. S. McLachlan, R. Clifton-Bligh, J. Morley, and S. Lal, "Stress watch: The use of heart rate and heart rate variability to detect stress: A pilot study using smart watch wearables," *Sensors*, vol. 22, no. 1, p. 151, 2021.

[43] J. A. Healey and R. W. Picard, "Detecting stress during real-world driving tasks using physiological sensors," *IEEE Transactions on intelligent transportation systems*, vol. 6, no. 2, pp. 156–166, 2005.

[44] Y. Chen and C. C. Yen, "Understanding the influence of stress on sedentary workers' sitting behavior in screen-based interaction context," in *Adjunct Publication of the 23rd International Conference on Mobile Human-Computer Interaction*, 2021, pp. 1–5.

[45] B. Choi, H. Jebelli, and S. Lee, "Feasibility analysis of electrodermal activity (eda) acquired from wearable sensors to assess construction workers' perceived risk," *Safety science*, vol. 115, pp. 110–120, 2019.

[46] L. V. Coutts, D. Plans, A. W. Brown, and J. Collomosse, "Deep learning with wearable based heart rate variability for prediction of mental and general health," *Journal of Biomedical Informatics*, vol. 112, p. 103610, 2020.

[47] K. M. Dalmeida and G. L. Masala, "Hrv features as viable physiological markers for stress detection using wearable devices," *Sensors*, vol. 21, no. 8, p. 2873, 2021.

[48] R. de Fazio, D. Cafagna, G. Marcuccio, A. Minerba, and P. Visconti, "A multi-source harvesting system applied to sensor-based

smart garments for monitoring workers' bio-physical parameters in harsh environments," *Energies*, vol. 13, no. 9, p. 2161, 2020.

[49] H. Feng, H. M. Golshan, and M. H. Mahoor, "A wavelet-based approach to emotion classification using eda signals," *Expert Systems with Applications*, vol. 112, pp. 77–86, 2018.

[50] T. Feng, B. M. Booth, B. Baldwin-Rodríguez, F. Osorno, and S. Narayanan, "A multimodal analysis of physical activity, sleep, and work shift in nurses with wearable sensor data," *Scientific reports*, vol. 11, no. 1, pp. 1–12, 2021.

[51] A. Gaballah, A. Tiwari, S. Narayanan, and T. H. Falk, "Context-aware speech stress detection in hospital workers using bi-lstm classifiers," in *ICASSP 2021-2021 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. IEEE, 2021, pp. 8348–8352.

[52] M. Gjoreski, M. Luštrek, M. Gams, and H. Gjoreski, "Monitoring stress with a wrist device using context," *Journal of biomedical informatics*, vol. 73, pp. 159–170, 2017.

[53] K. Heurtefeux, E. B. Hamida, and H. Menouar, "Design and implementation of a sustainable wireless ban platform for remote monitoring of workers health care in harsh environments," in *2014 6th International Conference on New Technologies, Mobility and Security (NTMS)*. IEEE, 2014, pp. 1–5.

[54] S. Hosseini, R. Gottumukkala, S. Katragadda, R. T. Bhupatiraju, Z. Ashkar, C. W. Borst, and K. Cochran, "A multimodal sensor dataset for continuous stress detection of nurses in a hospital," *Scientific Data*, vol. 9, no. 1, pp. 1–13, 2022.

[55] K. Hovsepian, M. Al'Absi, E. Ertin, T. Kamarck, M. Nakajima, and S. Kumar, "cstress: towards a gold standard for continuous stress assessment in the mobile environment," in *Proceedings of the 2015 ACM international joint conference on pervasive and ubiquitous computing*, 2015, pp. 493–504.

[56] E. Ertin, N. Stohs, S. Kumar, A. Raij, M. Al'Absi, and S. Shah, "Autosense: unobtrusively wearable sensor suite for inferring the onset, causality, and consequences of stress in the field," in *Proceedings of the 9th ACM conference on embedded networked sensor systems*, 2011, pp. 274–287.

[57] R. İLERİ and F. LATİFOGLU, "Analysis of the electrodermal activity signals for different stressors using empirical mode decomposition," *Academic Platform Journal of Engineering and Science*, vol. 8, no. 2, pp. 407–414.

[58] J. Birjandtalab, D. Cogan, M. B. Pouyan, and M. Nourani, "A non-EEG biosignals dataset for assessment and visualization of neurological status," in *2016 IEEE International Workshop on Signal Processing Systems (SiPS)*. IEEE, 2016, pp. 110–114.

[59] H. Jebelli, M. M. Khalili, and S. Lee, "Mobile eeg-based workers' stress recognition by applying deep neural network," in *Advances in informatics and computing in civil and construction engineering*. Springer, 2019, pp. 173–180.

[60] H. Jebelli, M. Habibnezhad, M. M. Khalili, M. S. Fardhosseini, and S. Lee, "Multi-level assessment of occupational stress in the field using a wearable eeg headset," in *Construction Research Congress 2020: Safety, Workforce, and Education*. American Society of Civil Engineers Reston, VA, 2020, pp. 140–148.

[61] E. E. Kaczor, S. Carreiro, J. Stapp, B. Chapman, and P. Indic, "Objective measurement of physician stress in the emergency department using a wearable sensor," in *Proceedings of the... Annual Hawaii International Conference on System Sciences. Annual Hawaii International Conference on System Sciences*, vol. 2020. NIH Public Access, 2020, p. 3729.

[62] J. Kent, A. Fong, E. Hall, S. Fitzgibbons, and J. Sava, "Measurement of trauma caregiver stress: Validation of hrv in a real-world surgical setting," *Journal of Surgical Research*, vol. 265, pp. 252–258, 2021.

[63] G. Lee, B. Choi, H. Jebelli, C. Ryan Ahn, and S. Lee, "Noise reference signal–based denoising method for eda collected by multimodal biosensor wearable in the field," *Journal of Computing in Civil Engineering*, vol. 34, no. 6, p. 04020044, 2020.

[64] V. Mozgovoy, "Stress pattern recognition through wearable biosensors in the workplace: experimental longitudinal study on the role of motion intensity," in *2019 6th Swiss Conference on Data Science (SDS)*. IEEE, 2019, pp. 37–45.

[65] K. Plarre, A. Raij, S. M. Hossain, A. A. Ali, M. Nakajima, M. Al'Absi, E. Ertin, T. Kamarck, S. Kumar, M. Scott *et al.*, "Continuous inference of psychological stress from sensory measurements collected in the natural environment," in *Proceedings of the 10th ACM/IEEE international conference on information processing in sensor networks*. IEEE, 2011, pp. 97–108.

[66] H. Sarker, M. Tyburski, M. M. Rahman, K. Hovsepian, M. Sharmin, D. H. Epstein, K. L. Preston, C. D. Furr-Holden, A. Milam, I. Nahum-Shani *et al.*, "Finding significant stress episodes in a discontinuous time series of rapidly varying mobile sensor data," in *Proceedings of the 2016 CHI conference on human factors in computing systems*, 2016, pp. 4489–4501.

[67] J. Shukla, M. Barreda-Ángeles, J. Oliver, and D. Puig, "Efficient wavelet-based artifact removal for electrodermal activity in real-world applications," *Biomedical Signal Processing and Control*, vol. 42, pp. 45–52, 2018.

[68] E. Smets, E. Rios Velazquez, G. Schiavone, I. Chakroun, E. D'Hondt, W. De Raedt, J. Cornelis, O. Janssens, S. Van Hoecke, S. Claes *et al.*, "Large-scale wearable data reveal digital phenotypes for daily-life stress detection," *NPJ digital medicine*, vol. 1, no. 1, p. 67, 2018.

[69] E. N. Smith, E. Santoro, N. Moraveji, M. Susi, and A. J. Crum, "Integrating wearables in stress management interventions: Promising evidence from a randomized trial." *International Journal of Stress Management*, vol. 27, no. 2, p. 172, 2020.

[70] F.-T. Sun, C. Kuo, H.-T. Cheng, S. Buthpitiya, P. Collins, and M. Griss, "Activity-aware mental stress detection using physiological sensors," in *Mobile Computing, Applications, and Services: Second International ICST Conference, MobiCASE 2010, Santa Clara, CA, USA, October 25-28, 2010, Revised Selected Papers 2*. Springer, 2012, pp. 282–301.

[71] T. Umematsu, A. Sano, S. Taylor, M. Tsujikawa, and R. W. Picard, "Forecasting stress, mood, and health from daytime physiology in office workers and students," in *2020 42nd Annual International Conference of the IEEE Engineering in Medicine & Biology Society (EMBC)*. IEEE, 2020, pp. 5953–5957.

[72] T. Umematsu, A. Sano, and R. W. Picard, "Daytime data and lstm can forecast tomorrow's stress, health, and happiness," in *2019 41st Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*. IEEE, 2019, pp. 2186–2190.

[73] A. W. J. van Kraaij, G. Schiavone, E. Lutin, S. Claes, and C. Van Hoof, "Relationship between chronic stress and heart rate over time modulated by gender in a cohort of office workers: cross-sectional study using wearable technologies," *Journal of medical Internet research*, vol. 22, no. 9, p. e18253, 2020.

[74] F. Wu, T. Wu, and M. R. Yuce, "Design and implementation of a wearable sensor network system for iot-connected safety and health applications," in *2019 IEEE 5th World Forum on Internet of Things (WF-IoT)*. IEEE, 2019, pp. 87–90.

[75] P. Zhang, F. Li, R. Zhao, R. Zhou, L. Du, Z. Zhao, X. Chen, and Z. Fang, "Real-time psychological stress detection according to ecg using deep learning," *Applied Sciences*, vol. 11, no. 9, p. 3838, 2021.

[76] K. Zhuo, C. Gao, X. Wang, C. Zhang, and Z. Wang, "Stress and sleep: a survey based on wearable sleep trackers among medical and nursing staff in wuhan during the covid-19 pandemic," *General psychiatry*, vol. 33, no. 3, 2020.

[77] G. Lee, B. Choi, H. Jebelli, and S. Lee, "Assessment of construction workers' perceived risk using physiological data from wearable sensors: A machine learning approach," *Journal of Building Engineering*, vol. 42, p. 102824, 2021.

[78] R. E. Klabunde. (2016) Autonomic innervation of the heart and vasculature. [Online]. Available: https://www.cvphysiology.com/Blood%20Pressure/BP008

[79] M. J. Shen, "The cardiac autonomic nervous system: an introduction," *Herzschrittmachertherapie+ Elektrophysiologie*, vol. 32, no. 3, pp. 295–301, 2021.

[80] S. for Psychophysiological Research Ad Hoc Committee on Electrodermal Measures, W. Boucsein, D. C. Fowles, S. Grimnes, G. Ben-Shakhar, W. T. Roth, M. E. Dawson, and D. L. Filion, "Publication recommendations for electrodermal measurements," *Psychophysiology*, vol. 49, no. 8, pp. 1017–1034, 2012.

[81] J. J. Braithwaite, D. G. Watson, R. Jones, and M. Rowe, "A guide for analysing electrodermal activity (eda) & skin conductance responses (scrs) for psychological experiments," *Psychophysiology*, vol. 49, no. 1, pp. 1017–1034, 2013.

[82] E. Babaei, B. Tag, T. Dingler, and E. Velloso, "A critique of electrodermal activity practices at chi," in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems*, 2021, pp. 1–14.

[83] Y. Hu, C. Converse, M. Lyons, and W. Hsu, "Neural control of

sweat secretion: a review," *British Journal of Dermatology*, vol. 178, no. 6, pp. 1246–1256, 2018.

[84] M. Kusserow, O. Amft, and G. Tröster, "Monitoring stress arousal in the wild," *IEEE Pervasive Computing*, vol. 12, no. 2, pp. 28–37, 2012.

[85] D. R. Dacunhasilva, Z. Wang, and R. Gutierrez-Osuna, "Towards participant-independent stress detection using instrumented peripherals," *IEEE Transactions on Affective Computing*, 2021.

[86] N. Banholzer, S. Feuerriegel, E. Fleisch, G. F. Bauer, T. Kowatsch *et al.*, "Computer mouse movements as an indicator of work stress: longitudinal observational field study," *Journal of medical Internet research*, vol. 23, no. 4, p. e27121, 2021.

[87] J. Hernandez, P. Paredes, A. Roseway, and M. Czerwinski, "Under pressure: sensing stress of computer users," in *Proceedings of the SIGCHI conference on Human factors in computing systems*, 2014, pp. 51–60.

[88] J. Zhao and E. Obonyo, "Convolutional long short-term memory model for recognizing construction workers' postures from wearable inertial measurement units," *Advanced Engineering Informatics*, vol. 46, p. 101177, 2020.

[89] P. E. Paredes, F. Ordonez, W. Ju, and J. A. Landay, "Fast & furious: detecting stress with a car steering wheel," in *Proceedings of the 2018 CHI conference on human factors in computing systems*, 2018, pp. 1–12.

[90] G. G. Berntson, J. Thomas Bigger Jr, D. L. Eckberg, P. Grossman, P. G. Kaufmann, M. Malik, H. N. Nagaraja, S. W. Porges, J. P. Saul, P. H. Stone *et al.*, "Heart rate variability: origins, methods, and interpretive caveats," *Psychophysiology*, vol. 34, no. 6, pp. 623–648, 1997.

[91] F. Shaffer and J. P. Ginsberg, "An overview of heart rate variability metrics and norms," *Frontiers in public health*, p. 258, 2017.

[92] A. J. Shah, R. Lampert, J. Goldberg, E. Veledar, J. D. Bremner, and V. Vaccarino, "Posttraumatic stress disorder and impaired autonomic modulation in male twins," *Biological psychiatry*, vol. 73, no. 11, pp. 1103–1110, 2013.

[93] Y. Liu, Y. Huang, J. Zhou, G. Li, J. Chen, Z. Xiang, F. Wu, and K. Wu, "Altered heart rate variability in patients with schizophrenia during an autonomic nervous test," *Frontiers in Psychiatry*, vol. 12, 2021.

[94] R. Lampert, "Ecg signatures of psychological stress," *Journal of electrocardiology*, vol. 48, no. 6, pp. 1000–1005, 2015.

[95] C. A. Frantzidis, E. Konstantinidis, C. Pappas, and P. D. Bamidis, "An automated system for processing electrodermal activity." *Studies in health technology and informatics*, vol. 150, pp. 787–787, 2009.

[96] M. P. Tarvainen, P. O. Ranta-Aho, and P. A. Karjalainen, "An advanced detrending method with application to hrv analysis," *IEEE transactions on biomedical engineering*, vol. 49, no. 2, pp. 172–175, 2002.

[97] A. Greco, G. Valenza, A. Lanata, E. P. Scilingo, and L. Citi, "cvxeda: A convex optimization approach to electrodermal activity processing," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 4, pp. 797–804, 2015.

[98] J. Shukla, M. Barreda-Angeles, J. Oliver, G. Nandi, and D. Puig, "Feature extraction and selection for emotion recognition from electrodermal activity," *IEEE Transactions on Affective Computing*, 2019.

[99] P. Schmidt, A. Reiss, R. Duerichen, C. Marberger, and K. Van Laerhoven, "Introducing wesad, a multimodal dataset for wearable stress and affect detection," in *Proceedings of the 20th ACM international conference on multimodal interaction*, 2018, pp. 400–408.

[100] H. F. Posada-Quintero, J. P. Florian, A. D. Orjuela-Cañón, T. Aljama-Corrales, S. Charleston-Villalobos, and K. H. Chon, "Power spectral density analysis of electrodermal activity for sympathetic function assessment," *Annals of biomedical engineering*, vol. 44, no. 10, pp. 3124–3135, 2016.

[101] N. E. Huang, "Introduction to the hilbert–huang transform and its related mathematical problems," in *Hilbert–Huang transform and its applications*. World Scientific, 2014, pp. 1–26.

[102] S. Mallat, *A Wavelet Tour of Signal Processing: The Sparse Way*. Academic Press, 2008.

[103] N. Ganapathy, Y. R. Veeranki, and R. Swaminathan, "Convolutional neural network based emotion classification using electrodermal activity signals and time-frequency features," *Expert Systems with Applications*, vol. 159, p. 113571, 2020.

[104] V. Sharma, N. R. Prakash, and P. Kalra, "Eda wavelet features as social anxiety disorder (sad) estimator in adolescent females," in *2016 International Conference on Advances in Computing, Communications and Informatics (ICACCI)*. IEEE, 2016, pp. 1843–1846.

[105] H. Pontzer, Y. Yamada, H. Sagayama, P. N. Ainslie, L. F. Andersen, L. J. Anderson, L. Arab, I. Baddou, K. Bedu-Addo, E. E. Blaak *et al.*, "Daily energy expenditure through the human life course," *Science*, vol. 373, no. 6556, pp. 808–812, 2021.

[106] C. M. Bishop, "Pattern recognition," *Machine learning*, vol. 128, no. 9, 2006.

[107] S. Albawi, T. A. Mohammed, and S. Al-Zawi, "Understanding of a convolutional neural network," in *2017 International Conference on Engineering and Technology (ICET)*. Ieee, 2017, pp. 1–6.

[108] H. Salehinejad, S. Sankar, J. Barfett, E. Colak, and S. Valaee, "Recent advances in recurrent neural networks," *arXiv preprint arXiv:1801.01078*, 2017.

[109] B. Liu, B. D. Tow, and I. M. Bonilla, "Molecular mechanism and current therapies for catecholaminergic polymorphic ventricular tachycardia," in *Cardiac Arrhythmias-Translational Approach from Pathophysiology to Advanced Care*. IntechOpen, 2021.

[110] K. Magtibay, X. Fernando, and K. Umapathy, "Enhancement of physiological stress classification using psychometric features." in *HEALTHINF*, 2022, pp. 430–437.

[111] H. Selye, "The general adaptation syndrome and the diseases of adaptation," *The journal of clinical endocrinology*, vol. 6, no. 2, pp. 117–230, 1946.

[112] ——, "Stress and the general adaptation syndrome," *British medical journal*, vol. 1, no. 4667, p. 1383, 1950.

[113] W. Raghupathi and V. Raghupathi, "Big data analytics in healthcare: promise and potential," *Health information science and systems*, vol. 2, no. 1, pp. 1–10, 2014.

[114] L. Qiu, S. H. M. Chan, and D. Chan, "Big data in social and psychological science: theoretical and methodological issues," *Journal of Computational Social Science*, vol. 1, no. 1, pp. 59–66, 2018.

[115] X. Zhang, Y. Wang, H. Lyu, Y. Zhang, Y. Liu, and J. Luo, "The influence of covid-19 on the well-being of people: Big data methods for capturing the well-being of working adults and protective factors nationwide," *Frontiers in Psychology*, vol. 12, 2021.

[116] K. Nkurikiyeyezu, A. Yokokubo, and G. Lopez, "The effect of person-specific biometrics in improving generic stress predictive models," *arXiv preprint arXiv:1910.01770*, 2019.

Karl Magtibay obtained his Bachelor's degree in Biomedical Engineering with honours (B.Eng., '12) and Master's degree in Electrical and Computering Engineering (M.A.Sc., '14) from Ryerson University, Toronto, Ontario, Canada. At the time of submission, Karl is pursuing his Doctor of Philosophy (Ph.D.) degree in Biomedical Engineering from Toronto Metropolitan University, Toronto, ON, Canada (formerly Ryerson University). Karl's research interests are in Biomedical Signal and Image processing, Biomedical Engineering, and Mathematical Modelling and Simulations.

Karthikeyan Umapathy is a Professor at Toronto Metropolitan University, Toronto, Ontario, Canada (Formerly Ryerson University). He received his Doctor of Philosophy (Ph.D.) degree in Electrical and Computer Engineering from the University of Western Ontario, Canada in 2006. He is a senior member of IEEE, Affiliate Scientist at St. Michael's Hospital (iBest). His research interests are in Biomedical Signal and Image Analysis, Time-frequency Analysis, Digital Signal Processing, Cardiac Electrophysiology, Magnetic Resonance Imaging, Feature Extraction and Pattern Classification, Medical Instrumentation, Health Analytics.