

# Quantifying Digital Biomarkers for Well-Being

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Wearable devices have become ubiquitous, collecting rich temporal data that offers valuable insights into human activities, health monitoring, and behavior analysis. Leveraging these data, researchers have developed innovative approaches to classify and predict time-based patterns and events in human life. Time-based techniques allow the capture of intricate temporal dependencies, which is the nature of the data coming from wearable devices.

LSTM

digital biomarkers

well-being

## 1. Introduction

Wearables, such as smartwatches, fitness trackers, and biosensors, have gained popularity due to their ability to continuously monitor various physiological signals and capture temporal patterns in real-time. This wealth of temporal data provides valuable insights into human activities, health monitoring, and behavior analysis and opens up new possibilities for personalized, context-aware applications that can continuously monitor and classify temporal patterns to support various domains, including healthcare, fitness, and productivity enhancement.

Human well-being monitoring and prediction <sup>[1]</sup> is one of the example application areas focusing on an individual's overall state of physical, mental, and social health, reflecting their sense of contentment, happiness, and fulfilment in life. World Health Organization (WHO) defines a well-being index (WHO-5) <sup>[2]</sup> with 5 factors based on the answers given to the following questions: 'I have felt cheerful and in a good spirit', 'Calm and relaxed', 'Active and vigorous', 'Woke up fresh and rested', 'Daily life interests me'. The answers range from 'All of the time' to 'At no time' with six possible inputs.

In recent years, there has been a growing interest in leveraging wearable devices to monitor and predict individuals' well-being and mental health in the literature <sup>[3][4][5][6]</sup>. This trend has emerged as a response to the increasing awareness of the importance of mental health in modern society and the growing data size collected by wearables. Traditional machine-learning algorithms, such as logistic regression, decision trees, and ensemble methods, have been extensively utilized in classifying or predicting well-being using data collected from wearables and questionnaires. However, the time aspect of the temporal data, in other words, how previous data impact future well-being levels, is often overlooked in related studies. Wearables offer a unique opportunity to collect longitudinal data, enabling a deeper understanding of how stress, anxiety, and emotional states fluctuate over time <sup>[7][8]</sup>. Time-based prediction techniques, when combined with wearable devices, can offer a unique opportunity to capture and analyze temporal patterns. This integrated approach can provide valuable insights into individuals' emotional states over time, facilitating early detection and timely interventions for improved mental well-being.

In addition, deep-learning architectures have emerged as powerful tools for time-based prediction problems. Recurrent Neural Networks (RNNs) and convolutional neural networks (CNNs) have gained attraction in well-being research [9][10][11][12][13][14]. RNNs, particularly LSTM variants, have demonstrated their ability to capture long-term dependencies and temporal dynamics in well-being-related data, while CNNs extract hierarchical features from wearable sensor data, enabling more accurate prediction. Furthermore, the combination of deep-learning architectures with wearable devices has led to the development of hybrid models that leverage both wearable sensor data and contextual information. These models incorporate multimodal inputs, such as physiological signals, accelerometer/activity data, and contextual features like time of day, location, social interactions, and self-reported mood states. By fusing multiple data sources that may impact an individual's well-being levels, the model's performance can be improved.

As well as deep-learning algorithms, ensemble methods are also powerful tools. Ensemble models combine multiple base classifiers to make predictions, leveraging the strengths of different models and reducing the impact of individual model weaknesses. Techniques like Bagging, Boosting, and Random Forests have been successfully employed in time-based classification tasks, yielding improved performance and robustness.

## 2. Quantifying Digital Biomarkers for Well-Being

Well-being, a multidimensional concept encompassing various facets of emotional and psychological health, has become a focal point of research [1][5][15][16][17] and early health intervention by continuous monitoring [18][19]. Within the spectrum of well-being, stress, anxiety, positive affect, and negative affect play pivotal roles in determining an individual's mental and emotional state [20][21]. Stress and anxiety can significantly impact one's overall well-being, and understanding and managing these factors are essential for promoting mental health [20][22][23].

Studies have explored the integration of wearable sensors, such as heart rate monitors, electrodermal activity sensors, accelerometers, and even Bluetooth beacons, to capture physiological and behavioral signals associated with stress and emotional well-being [24][25]. These sensors provide non-intrusive and continuous data streams that offer insights into individuals' emotional experiences and their positive and negative affect.

Nevertheless, the most studied factor is the stress in the literature [26][27][28][29][30][31][32]. In recent years, stress prediction and assessment have witnessed a surge in innovative research aimed at harnessing diverse data sources and cutting-edge machine-learning techniques. These efforts have collectively contributed to a deeper understanding of stress patterns across different contexts and data modalities, paving the way for more effective stress management strategies.

Investigating the feasibility of stress prediction based on behavioral data, researchers have delved into smartphone activity as a potential stress indicator [27]. Leveraging machine-learning algorithms, this study dissects smartphone behaviors to uncover stress-indicative patterns, therefore contributing to a deeper understanding of stress dynamics in the digital age. By focusing on digital behavior, the study presents a unique perspective on stress prediction, emphasizing the significance of smartphone interactions in capturing stress-related cues.

Wearable technology emerges as another avenue for stress prediction. Employing physiological sensors, studies have endeavored to predict and visualize work-related stress through wearable sensing [28]. Heart rate and skin conductance are monitored to develop models that provide real-time insights into stress levels, thus empowering individuals and organizations with tools for effective stress management. By focusing on physiological markers, this research offers a unique approach to stress prediction, emphasizing the importance of wearable technology in monitoring and mitigating stress.

Moreover, the analysis of physiological signals has yielded significant strides in stress detection under real-life conditions [29]. By scrutinizing heart rate variability and electrodermal activity, researchers provide valuable insights into physiological stress markers, enhancing researchers' understanding of stress dynamics in natural environments. This study's focus on physiological markers in real-life settings offers a nuanced perspective on stress detection, providing insights into stress responses beyond controlled environments.

Mobile sensing has also paved the way for predicting stressful life events by analyzing sensor data such as location and physical activity [30]. This novel approach enhances researchers' comprehension of stress-inducing contexts and contributes to users' overall well-being by identifying potential stress triggers. This approach shifts the focus from immediate stress levels to predicting stress-inducing situations, highlighting the potential of preemptive interventions.

Intriguingly, multimodal approaches have been explored by combining speech and wearable sensor data for stress detection [31]. By integrating speech features and physiological signals, researchers have showcased the potential of using multiple data sources to achieve more accurate stress prediction models. The study's emphasis on combining speech and physiological data offers a comprehensive approach to stress detection, leveraging multiple modalities to enhance prediction outcomes.

Comprehensive stress and sleep prediction strategies have incorporated physiological signals and smartphone data [32][33]. The fusion of heart rate variability, accelerometer data, and self-reported stress levels yields enhanced accuracy, demonstrating the potential of amalgamating diverse data sources for holistic stress assessment. This research stands out for its comprehensive integration of physiological signals and smartphone data, offering a multifaceted perspective on stress prediction [32]. In [33], the approach of combining wearables and phone sensors enables more accurate sleep detection by leveraging the benefits of both streams: combining wearable movement detection with mobile phone technology usage detection is employed. They showed that the combination of phone activity and wearables might produce better models of self-reported sleep than either stream alone on the Tesseract dataset.

There are also recent studies focusing on monitoring and predicting stress levels in the workplace. In a recent study [26], researchers developed a mobile app to collect a comprehensive dataset from 30 workers over 8 weeks. The app prompted users to complete a questionnaire three times daily, assessing stress, sleep quality, work abandonment, energy levels, and mood states. Unlike other studies, this research did not involve recording sensor, speech, or camera data. Instead, the focus was solely on the self-reported questionnaire responses.

One intriguing avenue of exploration is the utilization of surrounding stress-related data for predicting individual stress levels. Researchers have introduced a groundbreaking approach that capitalizes on personal and social stress-related data to achieve remarkable prediction accuracy [32]. It unveils the contagious nature of stress, shedding light on how one's focus can influence those around them. Unlike traditional stress prediction methods, which primarily rely on individual data, this study sheds light on the influence of surrounding stress, emphasizing the interconnectedness of stress levels within a social context at the workplace.

These studies underscore the richness and variety of approaches in stress prediction research. By leveraging different data modalities, advanced analytics, and machine-learning techniques, researchers aim to predict stress levels accurately and provide valuable insights into the intricate interplay of stress dynamics across workplaces, digital platforms, educational settings, and daily life. The cumulative efforts in this field contribute to a more profound comprehension of stress patterns and offer potential avenues for effective stress management and well-being enhancement.

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