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A Review of Supervised Learning for (Workplace) Mental Health and Wellbeing

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Abstract: Mental health problems such as anxiety and loneliness have seen a dramatic increase, despite the tremendous growth in the healthcare industry in recent years. Traditional methods of diagnosing mental health and wellbeing issues can be effective, but they are often very time consuming and labour intensive and require active patient participation. Recent research has demonstrated the power of utilising artificial intelligence and physiological/psychological data to diagnose and predict the mental wellbeing of individuals. This paper systematically reviews the applications of supervised learning techniques to predict mental health and wellbeing constructs, such as stress and anxiety, and their potential to support workplace wellbeing. Given that data are an integral part of supervised learning approaches, this paper also reviews data collection practices and relevant considerations, such as bias implicitly expressed by data, especially in a workplace environment. Additionally, the paper investigates the ethical nature and aspects of explainability of wellbeing support systems, which are particularly sensitive in this subject area. Based on these research objectives, the gaps in the literature are identified and future research directions are recommended, including explainable AI, environmental factors in wellbeing prediction and the ethical deployment of such systems in workplace settings.

Keywords: mental health and wellbeing, workplace wellbeing, supervised learning for mental health, supervised learning for workplace wellbeing

1. Introduction

The healthcare industry has seen tremendous growth in the past several years, especially during and after the COVID-19 pandemic. However, mental health–related problems continue to rise, with loneliness, anxiety, substance abuse and suicide rates increasing [1]. According to a 2015 study, mental health is one of the leading contributors to the overall global burden of diseases, out of 301 diseases [2]. The study also found that depressive disorders have a direct and indirect impact on life expectancy and quality of life [2].

Despite the significant burden mental illness places on people and its adverse effects on the quality of life, the reality is that the majority of people with mental illness worldwide are neglected or do not receive proper care [3]. This has inspired many researchers to conduct research in this field and has resulted in various methods and technologies to address this global problem.

Traditional techniques for assessing mental health and wellbeing typically include counselling sessions with psychologists and diagnostic interviews conducted by psychiatrists. However, such clinical visits are sometimes infrequent, giving clinicians very limited time to fully understand the patients' symptoms [4]. Additionally, recall bias is often encountered when patients are asked to describe their symptoms retrospectively. Diagnostic interviews often use a standardised classification system such as the DSM-5-TR [5] and ICD-11 [6]. Additionally, scientifically validated questionnaires are used to help understand and measure stress, depression and other symptoms. Examples of such questionnaires include the Patient Health Questionnaire (PHQ-9) [7] and the Quick Inventory of Depressive Symptomatology (QIDS) [8].

It can be challenging for people to seek help for their mental health using traditional approaches. Since the outbreak of the COVID-19 pandemic, its psychological impact has been observed across the globe. Various studies and surveys have shown that restrictive measures such as isolation, social distancing and quarantine during the pandemic have affected the mental wellbeing of people [2, 9, 10]. In addition, traditional assessment techniques require people to be aware of their mental wellbeing and actively seek help, but a majority of people are reluctant to do so due to the social stigma associated with mental health and illness [11].

The use of digital technologies and artificial intelligence (AI) as an alternative to traditional techniques for the diagnosis and prognosis of mental health and wellbeing is an area that has sparked the interest of the research community in recent years. This has led to new insights and thus innovations in clinical practice. Whilst psychology was previously overlooked when conducting physiological studies [12], recent research has shown that the two are interconnected and that a decline in psychological wellbeing negatively impacts a person's physiological state. For instance, whilst stress is difficult to quantify, studies have shown that feeling stressed can lead to increased skin conductance [13], reduced heart rate variability (HRV) [14] and decreased skin temperatures [15]. With the advancement of technology, various sensors have been used to monitor the physical and mental health of patients, and various AI technologies have been utilised to analyse data to gain a deeper understanding of the condition and symptoms.

This paper systematically reviews AI-enabled wellbeing and mental health diagnosis and prognosis methods to summarise trends and emerging best practices. Given that AI is a very broad topic and that it has been widely applied in the field of wellbeing and mental health, this paper focuses on reviewing the applications, adaptation and further development of supervised machine learning techniques in the field of workplace wellbeing. Given that labelled data are an integral part of supervised machine learning approaches, this paper

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also examines various data collection methods from different sources. Ethics and explainability aspects of this subject are very sensitive; thus, such important considerations when developing workplace wellbeing support systems are also discussed in this paper. The paper concludes by discussing the potential of existing supervised learning–enabled mental wellbeing support approaches in the workplace environment, and it also outlines future directions for research. It is noteworthy that when terms such as 'mental health and wellbeing' and 'mental healthcare' are used, they will only include a subset of clinical constructs, such as stress and anxiety, but do not include mental illnesses such as schizophrenia and bipolar disorder. A discussion of such mental illnesses, recovery from said illnesses and the application of machine learning in mental health is beyond the scope of this paper.

Figure 1 provides a visual representation of the scope and structure of this paper. The left side of Figure 1 shows the different approaches to gathering data, including both traditional and digital approaches. The traditional approach includes the gathering and monitoring of psychological data (questionnaires, counselling sessions, assessments, etc.) and contextual data (lifestyle, environments, etc.). The digital approach also includes contextual data, but this time, technology is used to help collect physiological data (general activity, sleep, etc.). These different data sources are then analysed and used to train supervised machine learning models (right side of diagram) to predict and understand clinical constructs such as stress and anxiety.

The rest of the paper is structured as follows: Section 2 discusses the methods used to explore relevant studies and research. Section 3 provides the basic psychological underpinnings that support this study. Section 4 reviews supervised learning approaches for mental health and wellbeing, including the data collection processes and the supervised learning algorithms commonly used in such studies. Section 5 reports on the potential of the reviewed approaches for workplace wellbeing support. Section 6 concludes the paper.

2. Literature Search and Selection Methodology

In support of this review, a comprehensive literature search was carried out to explore existing research on the application of supervised learning techniques in mental health and wellbeing. Although the intended focus was on workplace wellbeing, the available literature on this specific area was limited. Consequently, the search was expanded to include studies on general wellbeing and mental health that could have relevance or applicability to the workplace.

The search process involved manually searching open-access academic platforms, such as Google Scholar and ResearchGate, as well as publisher databases such as IEEE Xplore, SpringerLink and Elsevier's ScienceDirect. Various keyword combinations were used during the search, including terms such as 'supervised learning', 'mental health', 'wellbeing', 'AI for wellbeing', 'workplace stress detection' and 'machine learning for stress or emotion'.

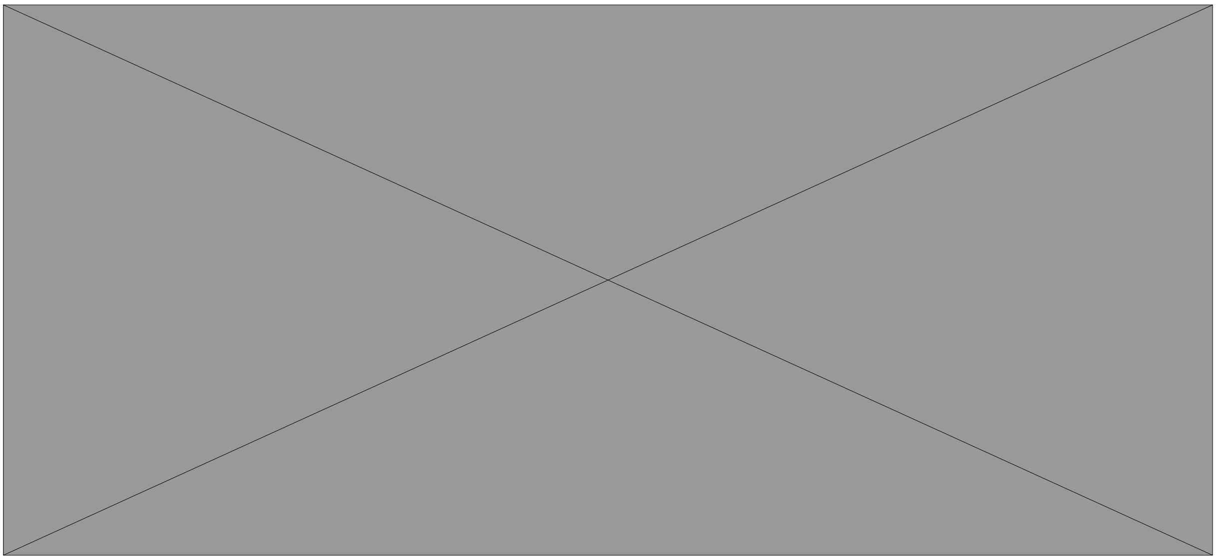
A large number of papers were initially reviewed, but only a subset was included in the final analysis based on relevance and scope. Studies were generally included if they applied supervised learning techniques to predict or classify psychological states, such as stress or anxiety, and if they used physiological, psychological, behavioural or environmental data. No restriction was placed on year of publication, although the majority of the reviewed studies were published between 2010 and 2023.

Studies focused purely on unsupervised learning, reinforcement learning or severe psychiatric conditions such as schizophrenia were excluded, unless they provided relevant methodological insights. The review process was iterative and exploratory, tailored to the availability and relevance of work at the time, and with particular attention to studies that could be adapted or extended to workplace wellbeing support.

3. Basic Psychological Underpinnings

The psychology of a person's health and wellbeing is undoubtedly a diverse multifaceted topic owing to subjective circumstances and individual differences. The scope of this paper is limited to the psychological considerations of conditions routinely related to the workplace environment, such as stress [16], which are introduced in this section. Stress can be considered physical, emotional or psychological strain, and occurs when an individual's psychological resources are inadequate to cope with the challenges arising from exposure to various physical or psychosocial stressors. Such stressors naturally vary according to specific situations; in an organisational context, it

Figure 1
Typical wellbeing and mental health diagnosis and prognosis methods reviewed



could result from poor workplace organisation, support, management or conditions [17].

Increased levels of stress amongst employees may also pose a risk for businesses, with potentially increased absenteeism and reduced job performance, as well as increasing the propensity for employees to develop mental health conditions such as depression, anxiety and burnout [18]. Workplace stress is additionally linked to cardiovascular disease [19], highlighting its negative physical consequences. Many factors may catalyse such issues, including the resulting impact of stigma and discrimination [20] or the poor handling of an employee's situation by those responsible for their management [21]. Furthermore, the increase in employees working from home following the COVID-19 pandemic emphasised that workplace stress is not limited to the physical workplace, with literature identifying the impact of familial relationships on work-related stress [22]. Occupational stress, therefore, presents as a vast, multifaceted issue with sombre ramifications for both employers and employees.

Clearly, reducing workplace stress is crucial for businesses if they want to operate efficiently at full capacity. Understanding, identifying and supporting employees through stress is paramount to reducing both its personal and organisational impact. It is, therefore, crucial to amass continuous data regarding employee stress levels to inform such analysis. Subjective measures, such as questionnaires, are commonly used to collect employee health data such as the self-applied Work Stress Questionnaire (WSQ) [23]. Such measures help management understand workers' stress levels and identify personnel at risk of stress-related absenteeism, and are also favourable because they are simple, efficient and low-cost to deploy [24]. However, potentially due to the aforementioned stigma associated with mental health, response bias is often observed in stress measurement questionnaires [25]. This suggests that data from multiple channels would be superior for an accurate evaluation of employee stress levels,.

One method of data collection is the use of biometric sensors to collect physiological information intrinsically linked to stress, such as heart rate (HR), temperature and electrodermal activity [26]. Studies have evaluated the implementation of sensors [27, 28], with contemporary research proposing the use of unobtrusive devices [29] or passive sensors [30] to eliminate the associated concerns about intrusiveness. The implementation of a system that collects sensor data and applies frequent subjective stress questionnaires will provide a more comprehensive evaluation of employee mental health, augment workforce management and inform any resulting administrative decisions. Undoubtedly, it would be beneficial to integrate elements of explainable AI (XAI) into such a system, which is generally becoming standard practice to increase transparency and assist users in interpreting and understanding the outputs of machine learning techniques [31]. However, this may be even more imperative in the field of mental health and wellbeing, as there are probabilistic relationships between data related to issues and disorders and their symptoms and outcomes [32]. Thus, explainability is crucial for the correct understanding of the output so as to develop a trustworthy and therefore useful system.

4. Supervised Learning for Mental Wellbeing

AI is a broad topic, ranging from symbolic reasoning and robotics to machine learning, natural language processing and so on. Over the past two decades, there has been a surge of interest in the use and application of AI, particularly machine learning methods, in healthcare, with many groundbreaking new works emerging. As mentioned above, the discussions in this paper are limited to supervised learning approaches using labelled datasets targeting mental health and wellbeing, which utilise either conventional machine learning algorithms or recently proposed deep learning architectures. The two key elements of a typical supervised learning approach to mental health and wellbeing are data collection and machine learning model development, which are described in detail in the remainder of this section.

4.1. Sourcing data from multiple channels

Whilst the algorithm or architecture employed in supervised learning to make predictions or analysis is important, data also plays a crucial role. There is a strong relationship between the data that is fed into a system and the result that comes out of it. Often, biases in machine learning are not due to poor system design, but rather due to bias hidden within the data. A recent study conducted in 2020 by Slota et al. [33] reports the findings of interviews conducted with various stakeholders in the field of AI to understand the failures and successes of AI systems. One of the key points that repeatedly come up is data quality. Therefore, data collection, followed by cleaning and processing, becomes one of the most important stages when training supervised learning models.

A wide variety of factors influence mental health and wellbeing, and these factors can be difficult to measure. Consequently, over the years, various approaches have been applied to different types of data from varying sources in an attempt to develop effective solutions in this problem area. Data collection and monitoring of mental health and wellbeing can be broadly divided into two categories: the traditional approach and the technology-assisted approach.

4.1.1. Traditional approach

From this perspective, collecting data with the help of scientifically validated questionnaires can provide rich information as well as a rating or score of an individual's mental state and health. Examples of such questionnaires include the Beck Depression Inventory [34], Patient Health Questionnaire [7], QIDS [8] and Perceived Stress Scale [35]. In addition to this, psychologists require individuals to attend one-on-one sessions to analyse their behaviour and understand their mental state. Whilst the use of validated questionnaires and counselling sessions provides a strong basis for diagnosis and prognosis of mental health and wellbeing, this approach often suffers from the high requirement of time and associated resources. Completing questionnaires and analysing the answers is time consuming and laborious for both the participant and psychologist. Furthermore, when conditions or mental states are self-reported, recall bias can significantly distort the results.

4.1.2. Technology-assisted approach

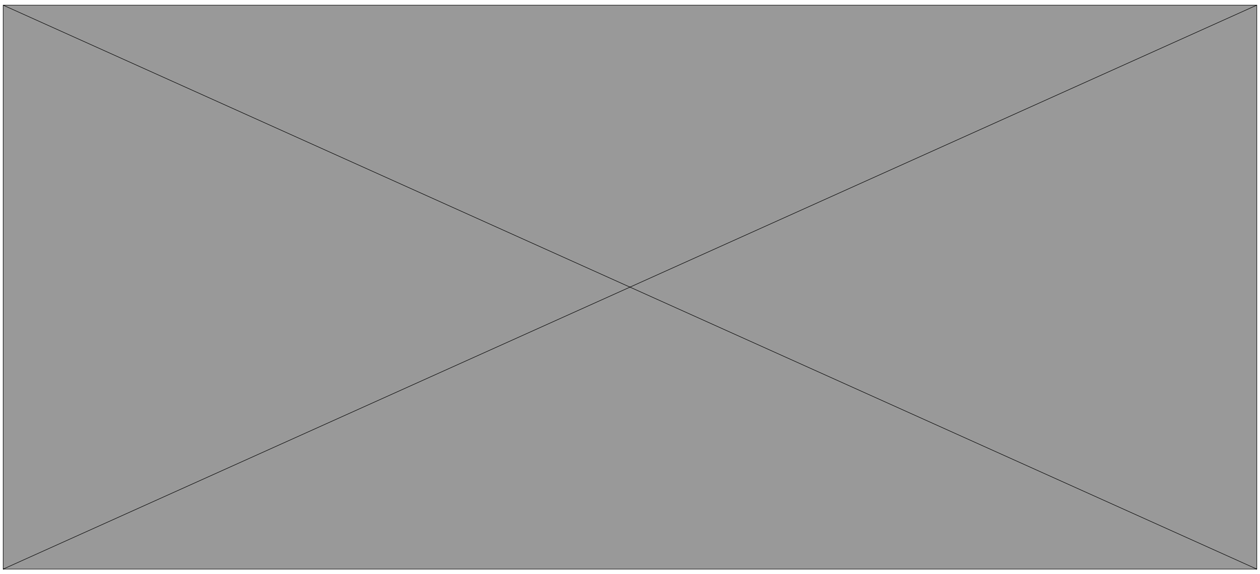
Technology-assisted mental health and wellbeing monitoring is an effective approach to overcome challenges faced by the traditional approach, but it also provides a clearer understanding of all the factors that influence an individual's mental state. One of the simplest ways to integrate technology is through self-reporting and self-assessment functionalities enabled by mobile applications, or Apps [36]. Mobile Apps such as Calm[1] and Headspace[2] provide tools and guidance for individuals to self-assess and improve their mental health and wellbeing. However, one of the biggest disadvantages of such mobile Apps is that there remains uncertainty about whether their results or guidance have a sufficiently strong scientific base.

Another way to integrate technology would be to use various commonly found sensors to collect relevant data, which can then be analysed. Mohr et al. [37] discussed the use of ubiquitous sensors on smartphones and wearable devices to collect and analyse data to better understand mental health. This paper proposed a layered, hierarchical framework that shows how raw sensor data can be converted into information-rich features, or behavioural markers [37]. This overall framework is depicted in Figure 2.

Based on this work, machine learning can be used to identify behavioural markers through these features, and initially use self-

[1] https://www.calm.com/
[2] https://www.headspace.com/

Figure 2
Layered hierarchical framework for processing raw sensor data into behavioural markers



reported mood or other markers from users as labels. Sensor data and other information, combined with labels, create a training sample that can be used to train supervised learning models. From here, both features and behavioural markers are used jointly to diagnose clinical conditions. Recent reviews have summarised real-time stress detection pipelines based on wearable physiological data and reported promising, yet heterogeneous, performance across algorithms and settings [38]. Recent results also show that adding contextual features (e.g., activity, location, time of day) to wearable signals improves stress detection performance [39].

One-on-one sessions with individuals give psychologists and psychiatrists the opportunity to perceive and understand the individual's behaviour. Understanding behavioural patterns is key to deciphering a person's mental state. Bone et al. [40] discussed the importance and utility of signal processing to understand mental health. They argued that noisy signal data from all sources (visual, auditory and physiological) hold valuable information on an individual's hidden mental traits and states [40] and stated that signal processing can help map raw data into representations of mental states and behaviours. Figure 3 shows the mental state prediction process proposed by Bone et al. [40]. An individual's mental state affects their behaviour. This behaviour is sampled using various signal processing techniques. Raw signal data from all sources are then localised, denoised and modelled to extract meaningful information.

With accurately labelled data, most machine learning algorithms are able to handle multiple sources of variable data in order to make accurate predictions. According to Bone et al. [40], the explainability of supervised learning models is of vital importance in healthcare and any end-to-end system must be able to explain how it makes decision. One of the advantages of signal processing is its interpretability. Most signal processing algorithms incorporate human knowledge when generating features and modelling data. By combining knowledge of human behaviour with proper signal processing algorithms, it is believed that Behavioural Signal Processing (BSP) can help augment the diagnostic ability of clinicians. However, despite the improved interpretability of BSP, no signal processing algorithm can account for variability in the data space. To resolve this concern, machine learning, including deep learning algorithms, needs to be adopted.

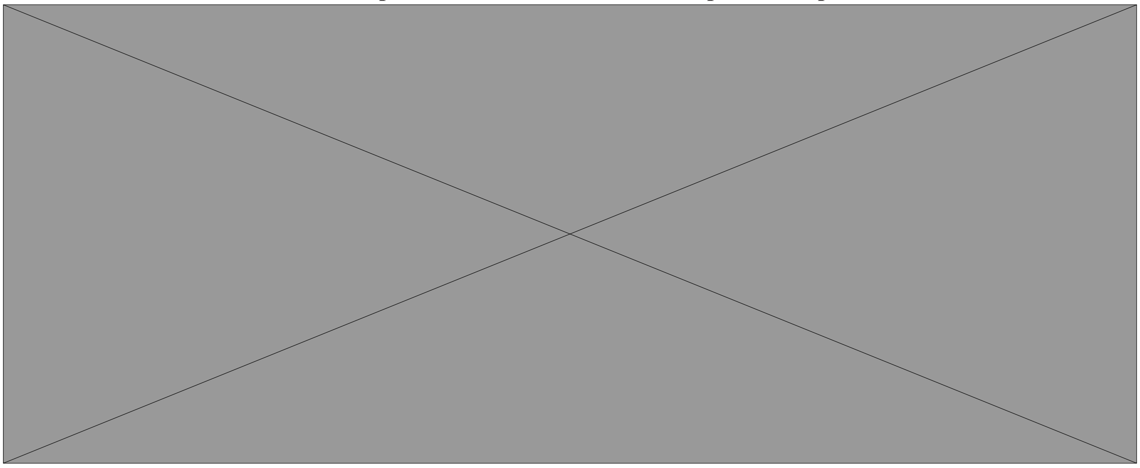
An individual's mental state and health are influenced by many factors and could vary frequently, even through a narrow window of time. As such, a holistic approach to understanding mental health and wellbeing using AI requires data collection across a combination of different channels, such as questionnaires and sensors (wearable, physiological, facial, speech, environmental, etc.). Actually, multimodality data and multi-sourced single modality data have been successfully employed in many areas, including the field of mental health and wellbeing, to ensure rich and useful features for data processing.

4.2. Physiological data

One of the primary benefits of utilising the technology-assisted approach to monitor and support mental health is that it enables a better understanding of the relationship between the psychological and physiological aspects of an individual. Most recent studies use certain physiological signals when attempting to detect and predict mental states and stress. Common physiological signals include HR and HRV, skin temperature [41] and galvanic skin response (GSR) (skin conductance) [26]. Electrocardiogram (ECG), electromyogram (EMG), photoplethysmogram (PPG) and electroencephalography (EEG) signals are often monitored in various studies to understand the physiological conditions and monitor other physiological signals such as HRV, HR, etc., as well as brain signals and brain activity. Nonetheless, accuracy varies across consumer devices and activities; recent meta-analysis and systematic reviews have highlighted non-trivial errors in HR and HRV and recommend validation in target populations [42].

Over the past decade, EEG has been widely utilised to analyse physiological and psychological activities. Briefly, EEG signals measure the electrical activity in the brain with the use of small electrodes attached to the scalp. A major advantage of EEG signals is the real-time response to external stimuli, which makes it possible to collect data in a pre-designed and controlled experimental environment setting. By monitoring and measuring electrical brain activity, an individual's response to external stimuli that correspond to their psychological state can be comprehensively analysed. However, one of the disadvantages

Figure 3
Schematic representation of the mental state prediction process



of utilising EEG signals is the significant effort necessary to carefully process the data and extract meaningful information. Additionally, the time, resources and expertise needed to set up the EEG systems create an additional barrier to data collection. Over the years various studies have successfully utilised EEG signals to predict different mental states, such as happiness, sadness, stress, fear, etc. [43, 44]. Recent studies have found success by combining EEG and other physiological signals such as HR, HRV and skin conductance [41, 43, 45, 46].

Widely used data collection devices for physiological data are summarised in Table 1. Most of the studies listed in Table 1 have attempted to detect or predict either stress or emotions in individuals based on physiological signals and have achieved good levels of success. A study published in 2023 [42] discussed the efficacy of wrist-worn devices in calculating physiological data such as HR.

With the advancement of technology, commercially available wearable devices, such as those manufactured by Fitbit, Garmin and Apple, can monitor and record various physiological signals of individuals with the use of ubiquitous sensors. Adopting this wearable technology for data collection can significantly reduce equipment costs and provide reliable, continuous data, as well as provide researchers with access to a large number of readily available participants across the globe.

Although data collection technologies are widely used, only a small portion of the data is publicly available. Existing open-source physiological datasets for stress and emotion detection include

Table 1
Physiological data collection devices commonly used in studies

Device Name	Physiological Data Signals	Studies/ References
Emotiv	EEG	[47]
Empatica device	HR, blood volume pulse (BVP), interbeat interval (IBI), ST, acceleration	[48]
WaveGuard EEG cap	EEG	[49]
Polar H7 chest band	HR, ECG	[50]
BioNomadix module	PPG, HR, multi-signal	[51]

1) WESAD (Wearable Stress and Affect Detection) Data Set [52]: Multimodal dataset with various physiological signals and motion data
2) Daily Ambulatory Psychological and Physiological recording for Emotion Research (DAPPER) dataset [53]: Psychological and physiological data for emotion identification
3) Multilevel Monitoring of Activity and Sleep in Healthy people (MMASH) dataset [54]: Psychophysiological data with psychological characteristics such as anxiety and stress
4) UBFC-Phys dataset [55]: Psychophysiological data to identify social stress
5) POPANE dataset [56]: Psychophysiological responses to positive and negative emotions for 1157 participants
6) Stress-Predict dataset [28]: Wrist-based PPG and multimodal stress annotations in free-living conditions
7) Nurses Multimodal Dataset [26]: Multimodal dataset collected from nurses in real hospital environments

Recently, a three-stage validation pipeline from laboratory to real-life free-living was proposed for stress wearable devices [57], which strengthens the ecological validity of such datasets.

4.3. Supervised learning techniques

Supervised learning is a type of learning in which an algorithm aims to learn the mapping between input features and output features through examples (i.e. a training dataset) and is able to modify its perceived relationship between the input and output by comparing the generated output to the original target point [58]. Classification and regression are two broad categories of supervised learning. Classification algorithms learn the relationship between an input feature vector and known classes (i.e. types of labels), while regression algorithms attempt to determine the strength and nature of the relationship between an input feature vector (i.e. independent variables) and a scalar value (i.e. dependent variable). Typical supervised learning approaches for mental health and wellbeing are summarised below.

4.3.1. Support vector machines

Amongst the supervised learning algorithms observed in this review , support vector machines (SVMs) frequently appear in various studies, indicating that this field has a wide range of applications [59–61]. SVM is a supervised learning algorithm that attempts to find the optimal decision boundary to separate the classes in the data [62]. SVM is a versatile and powerful algorithm, that can handle both unstructured and structured data. It can also solve linear and non-linear problems and is not prone to overfitting. Compared to other traditional machine learning algorithms such as decision trees, SVMs are generally more memory efficient and highly effective with data of high dimensionality.

4.3.2. Naïve Bayes

Naïve Bayes is a popular machine learning algorithm that is implemented by a network of applications of the Bayesian theorem, each calculating the probability of a hypothesis based on prior knowledge. Since it is a direct application of the probability theory, it is one of the simplest models and can work with even small amounts of data. Studies by Egilmez et al. [50] and Saeed et al. [63] used Naïve Bayes to predict stress based on given input data.

4.3.3. K-nearest neighbours

K-nearest neighbours (KNN) [64] is a non-parametric machine learning algorithm in which the prediction or outcome for a new data query is calculated based on its closest neighbours in the feature space. The number of neighbours to consider is chosen during the training process. The output class is determined by considering the majority class among the nearest neighbours. KNN is a simple yet very effective machine learning algorithm that has been widely used in various studies to identify stress in individuals [27, 61, 65].

4.3.4. Decision trees

Decision trees are another popular machine learning algorithm that learns by building a tree of decisions, where the leaf nodes represent the outcome (prediction) [66]. They are highly interpretable and easy to visualise, making them ideal for building models that need to be explainable. Although decision trees are prone to overfitting compared to models such as SVM, they have also been applied in stress detection research and have demonstrated their practicality [67].

4.3.5. Ensemble learning

Ensemble learning [68] involves combining multiple machine learning models to improve performance. By combining different models, higher or more accurate performance can usually be achieved because the errors of the individual models can be cancelled out [68]. A popular type of ensemble learning is Random Forests, in which multiple decision trees are trained on different subsets of the data to increase performance and make the model more robust. Similar to decision trees, random forests can also be easy to interpret. Ensemble learning has been widely and successfully used in various fields. Studies by Can et al. [27], Gjoreski et al. [48], and Havaei et al. [69] have all successfully incorporated ensemble learning to predict stress.

4.3.6. Logistic regression

Logistic regression is a popular and widely used binary classification algorithm, which means that given a data point, it can predict between 2 classes. The algorithm calculates the probability of all possible output classes using a logistic function, which uses an optimisation algorithm such as gradient descent to implement the mapping between input features and the outputs. Then the class with the highest probability will be selected as the final output. Due to its simplicity and interpretability, it has been widely used for various classification problems over the years. Studies by Rodríguez-Arce et al. [60] and Benchekroun et al. [70] have applied logistic regression to predict stress. One disadvantage of logistic regression is that it can struggle to capture complex non-linear relationships present in the data [4].

4.3.7. Neural networks

Neural networks are machine learning algorithms that have been inspired by the biological neural network. They follow a similar structure with interconnected nodes (neurons) that perform computations on input data and produce output signals [71]. Over the past decades, due to the rapid advances in computing equipment, neural networks have undergone significant evolution, from basic feedforward networks to convolutional and deep neural networks. Neural networks can be used in a very versatile way, and they are powerful models that can learn complex relationships and patterns from data, despite their high consumption of computational power. Because of this, neural networks have found a place in almost every field as models that can extract information and achieve very high levels of accuracy or performance. The disadvantages of neural networks are that they are often data-hungry algorithms, requiring large amounts of data for training. Additionally, it is a challenge to interpret the results or explain why the network predicted a certain class/output. This lack of explainability is one of the most significant reasons hindering its widespread application in the healthcare and wellness sector. Nevertheless, studies using neural networks to predict stress and anxiety have been reported [39, 72]. "Building on this, the recent work [73] proposes supervised contrastive frameworks (e.g., StressCon) that enhance stress detection robustness in wearable data. Complementary personalisation strategies based on self-supervised pretraining and sector adaptation have also improved individualized stress recognition from mobile sensing data [74].

Whilst a wide range of algorithms have been used in the papers that were reviewed, SVMs were amongst the more frequently applied methods and often yielded promising results in classifying stress and emotional states.

Note that unsupervised learning has also been employed for mental wellbeing support, such as the work reported in Reference [75], but a discussion of these is beyond the scope of this paper. Additionally, recent advancements in semi-supervised learning and large language models are opening new possibilities in mental health research, particularly in contexts where labelled data is scarce. Although this paper focuses solely on supervised learning, future reviews should consider these alternative paradigms, which may offer complementary strengths in complex and sensitive areas such as workplace wellbeing.

Although many papers discuss the use of supervised learning to classify and predict individuals' psychological states, relatively few studies have focused solely on workplace wellbeing. However, the basis for predicting stress, anxiety or emotions based on physiological signals will follow a similar style, with only slight variations in direction. When collecting data from employees , it is important to ensure that the data collection tool is unobtrusive and does not distract the individual while at work. This rules out EEG as a data source due to the onerous process of applying an EEG device and extracting reliable data. As more studies focus on data collected from wearable sensors and smartwatches, this indicates the future direction of data collection that will support supervised learning for workplace wellbeing.

5. Workplace Wellbeing Support

5.1. Ethical implications

Implementing employee wellbeing systems that involve data collection can provide clear benefits to both employers and their employees. However, these systems also raise important ethical concerns that must be carefully considered. Under data protection laws such as the General Data Protection Regulation (GDPR), most data collected from employees are classified as personal or sensitive. Health-related data, in particular, is explicitly defined as sensitive data in the GDPR (Article 9) due to the potential risk it poses to individual rights and freedoms. Therefore, any data collected through the channels discussed in this paper must be stored securely and processed in a lawful, fair and transparent manner[3], in strict compliance with the GDPR, to avoid legal or regulatory penalties [76].

Beyond legal compliance, such systems raise questions about employee privacy, consent, and power dynamics. If employees wish to keep their health data private, this decision may be seen as counterproductive behaviour [77], leading to tension or prejudice. Moreover, fear of being monitored, misunderstood or judged can discourage participation, increase stress and even undermine the intended purpose of the system. In some cases, this may lead to workplace stigma, false assumptions or social exclusion [11].

To mitigate these risks, wellbeing initiatives must be communicated in ways that highlight their benefits and ensure that employees understand that participation is voluntary, anonymous and compliant with data protection laws [78].

Beyond privacy concerns, the ethical use of AI itself must be addressed. Issues such as fairness, inclusivity, accountability and transparency are crucial [79, 80]. Machine learning models can unconsciously encode biases, making it difficult to detect or correct. Organisations must ensure that any predictive models are carefully validated to avoid harming individuals through false positives or negative results. Effective implementation requires a strong understanding of the organisation's operations, workforce and culture to circumvent unintended consequences [81]. When responsibly designed and applied, such systems can support improved employee wellbeing and better organisational outcomes.

5.2. Explainability

A major challenge in applying machine learning approaches to mental health and wellbeing is the transparency and trustworthiness of the algorithms. To overcome this challenge, the performance of the implemented algorithms must be evaluable even by laypeople who are not machine learning experts, so that they can decide whether to trust the outputs or not [82]. A key advantage of machine learning systems is their ability to analyse large amounts of data quickly and efficiently and make fast decisions. However, machine learning models are still susceptible to making false and inaccurate predictions and decisions. The cost of misdiagnosis in the field of mental health and wellbeing is often higher than generally believed. Thus, explainability becomes a key component of machine learning models in the field of mental health and wellbeing.

Explainability has been briefly discussed in an earlier section of this paper, but before further discussion on this topic, it is necessary to make clear the meaning of an explainable model. Explainability can mean different things to different groups of people, from the developers of algorithms to the users of models, such as psychologists, clinicians, employers and employees. For the latter group, a good explanation might mean making decisions that are consistent with clinical constructs (such as evidence of a better or worse clinical state) before presenting the output [83]. Although the explanation provided by the model may not entirely coincide with the clinical constructs, it is still important to at least know the individual feature or group of features that led the model to predict a certain outcome. Supported by the understanding of the predicted outcomes (i.e. the explainability of feature correlations), discrepancies between machine learning predictions and clinical constructs can sometimes lead to interesting new findings, which may also help to better support workplace wellbeing.

Supervised learning algorithms can be either interpretable or uninterpretable (i.e. black box models). Models such as decision trees are highly interpretable, making it easy to explain how the outcome was reached. On the other hand, models such as deep neural networks can extract more information from the data but are unable to explain the logic process behind the outcome in a human-readable format. This leads to the trade-off between model performance and model explainability when selecting supervised learning models for a workplace wellbeing support system [80]. A recent scoping review in mental health catalogues XAI techniques used by healthcare stakeholders and highlights persistent gaps in user-centred evaluations [84].

SVMs, which were commonly used in the reviewed studies, occupy a middle ground in this trade-off. Whilst not as inherently interpretable as decision trees, they are generally more transparent than deep neural networks and can offer strong performance, particularly when working with structured physiological data. However, the reasoning behind their decisions is still not readily accessible to non-technical users, which may limit their standalone use in sensitive wellbeing contexts unless accompanied by additional interpretability tools.

Transparency is a related concept to explainability, and they both play a role in the trustworthiness of a supervised learning model. These three characteristics are all pivotal for a successful workplace wellbeing support system. To make a supervised learning algorithm or model transparent, all its important features must be fully disclosed [83]. This includes how the model is structured and trained, how the data is collected, how biases within the data are scrutinised and what common assumptions are made by the system.

5.3. Discussions

As discussed in this paper, a wealth of research has been reported in the field of mental health and wellbeing support, but little research has focused specifically on workplace wellbeing. This was evident in the literature search process, where relatively few studies used supervised learning methods to directly address workplace mental health. As such, the scope of this review was broadened to include general studies on mental health and wellbeing, with a view that the insights and technologies presented in these studies could be adapted or extended to the workplace context.

Many of the works reviewed explored the use of physiological and behavioural signals to assess mental states such as stress or anxiety; these constructs are directly relevant to employee wellbeing. For example, several studies involved passive sensing using wearable devices or mobile Apps, which are suitable for workplace environments due to their unobtrusiveness and scalability. Recent evaluations with free-living wearable data further demonstrate the feasibility outside of laboratory settings, where class imbalance and annotation noise are identified as major challenges [85]. Although these studies were not always conducted in the workplace context, their methodologies and findings are applicable when considering organisational wellness interventions or monitoring frameworks.

Furthermore, the emphasis on using data from multiple channels and interpretable models in the reviewed literature has significant relevance for workplace applications, where transparency and ethical deployment are critical. For organisations, models that can offer explainability, operate non-intrusively and integrate with existing HR or occupational health frameworks represent a promising direction, even if the initial studies were developed without the workplace context in mind.

This gap in workplace-specific literature highlights a clear opportunity for future research. As work environments become increasingly digitalised, the development and evaluation of supervised learning systems tailored particularly for occupational settings and tested with employee populations will be essential. In particular, further work is needed to assess how environmental factors, such as noise, light and social dynamics, influence wellbeing in real-world workplaces

[3] https://gdpr.eu/what-is-gdpr/

and how these can be integrated with physiological and psychological signals to create more holistic AI-driven support systems.

Additionally, another gap identified was the lack of options for open-source workplace-specific wellbeing data. Whilst several open-source datasets are publicly accessible as discussed in this paper, there is a need for large-scale, high-quality mental health and wellbeing data collected from various wearable devices. These data also need to be labelled and validated with the help of psychologists. To achieve this, industry and academia need to work together to come up with an innovative yet practical solution. The availability of such data will enable more researchers to develop and evaluate supervised learning models, and thus accelerate the research into workplace wellbeing support. Systematic reviews in occupational health and safety further argue that AI applications remain under-validated in real-world workplaces, highlighting the need for rigorously tested wellbeing systems [86].

6. Conclusion

The primary objective of this paper was to survey studies that utilised supervised learning for mental health and wellbeing in the workplace. However, there is a dearth of research investigating supervised learning models in employee health and wellbeing. As such, this paper systematically reviewed articles that, in general, applied supervised learning technologies to predict or identify psychological states such as stress. Workplace mental wellbeing systems can be developed by adapting, extending and further developing the reviewed systems with minor revisions, such as the application of non-intrusive data collection approaches to not distract employees from their work. The paper refrained from discussing more serious mental health issues, such as schizophrenia or bipolar disorders, as they were out of the scope of the paper.

It is observed that most of the papers do not discuss the ethical nature or explainability aspects of their systems and models, which should be a key component moving forward. With the application focused on mental health and wellbeing, extra care must be taken to ensure that all developed systems and algorithms are trustworthy and explainable, as the cost of errors in judgement could be high.

Based on the surveyed literature, the application of supervised learning methods to the field of mental health and wellbeing shows tremendous promise and growth. Through appropriate models and by achieving the right balance between model performance, model explainability and trustworthiness, significant advancements in the detection and diagnosis of mental health for individuals can be achieved. Furthermore, with the use of common sensors such as smartwatches and fitness trackers, these tools and models can also be made available to the general public, which, supported by carefully staged messages, can help reduce the stigma associated with mental health.

Based on this review, three important areas have emerged as key directions for future research:

1) The development of XAI models that both organisations and employees can trust.
2) The integration of environmental factors alongside physiological and psychological signals to better understand workplace wellbeing.
3) The ethical implementation of AI systems that respect privacy, autonomy and fairness.

These aspects are essential for the responsible and effective application of supervised learning in the field of occupational wellbeing.

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Conflicts of Interest

The authors declare that they have no conflicts of interest to this work.

Data Availability Statement

The data that support the findings of this study are openly available in MAHNOB HCI-Tagging at https://doi.org/10.1109/T-AFFC.2011.25, reference number [10]; DEAP at https://doi.org/10.1109/T-AFFC.2011.15, reference number [66]; WESAD at https://doi.org/10.1145/3242969.3242985, reference number [82]; DAPPER at https://doi.org/10.6084/m9.figshare.13803185, reference number [12]; MMASH at https://doi.org/10.3390/data5040091, reference number [61]; UBFC-Phys at https://doi.org/10.1109/TAFFC.2021.3056960, reference number [80]; POPANE at https://doi.org/10.6084/m9.figshare.17061512, reference number [4].

Author Contribution Statement

Rohit Venugopal: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Dan Roll:** Conceptualization, Software, Formal analysis, Writing – original draft. **Mark J. Flynn:** Conceptualization, Methodology, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Project administration. **Phillip G. Bell:** Conceptualization, Resources, Writing – review & editing, Supervision. **Longzhi Yang:** Conceptualization, Validation, Resources, Writing – review & editing, Visualization, Supervision.

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