P2DS: A Holistic Approach to Psychiatric Disease Detection in Community Pharmacies

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Keywords: Post-Traumatic Stress Disorder, Depression, Burnout, Smart Wearables, Emotion Recognition, Artificial Intelligence.

Abstract: Health workers appear to have an increased risk of developing psychiatric diseases, namely Post-traumatic stress disorder (PTSD), Depression and Burnout, due to the nature of their job. In recent years, several approaches based on artificial intelligence have emerged, using facial expression, audio, text and physiological features to detect depression, stress and burnout. However, most of these solutions have limitations in their capacity to simultaneously detect multiple diseases, are not widely implemented in healthcare settings, and, in some cases, lack explainability. To address this challenge, we propose Psychiatric Disease Detection System (P2DS), a holistic rule-based system capable of detecting PTSD, Depression and Burnout in community pharmacists, combining emotion recognition, physiological and performance-related features. The set of rules developed to detect each disease is based on the most objective medical literature available, making the system explainable and suitable for healthcare environments.

1 INTRODUCTION

The World Health Organization (WHO) defines health workers as people whose work is destined to improve health. Those include doctors, nurses, pharmacists and technicians (World Health Organization, 2022). There is increasing evidence that health workers have an elevated risk of developing psychiatric illnesses, mainly Depression and Post-Traumatic Stress Disorder (PTSD), and Burnout syndrome, in great part due to the multiple risk factors present in their job (Hill et al., 2022; Razu et al., 2021; World Health Organization, 2022). These include increasing workload, long shifts, an accelerated pace of work and lack of support (Søvold et al., 2021). The presence of the aforementioned diseases imposes serious consequences, namely poorer patient care, increased work-related mistakes, increased absenteeism and greater patient dissatisfaction (Gregório et al., 2017; Samir AlKudsi et al., 2022; Søvold et al., 2021).

In past years, researchers have developed multiple systems to detect or predict psychiatric diseases. These systems use physiological, audio and image data, combined or separately, which is then run through machine learning models to predict diseases (Saganowski et al., 2023). Literature indicates that these systems have revolved around pre-established datasets and single disease detection. They have been tested in patients, students, nurses, and corporate staff (Chikersal et al., 2021; Eom et al., 2023; Francese & Attanasio, 2022; Otsuka et al., 2023a; Yang et al., 2020). Therefore, a gap in testing is noted in a community pharmacy setting.

Hence, we propose Psychiatric Disease Detection System (P2DS), a holistic system capable of detecting and alerting for the presence PTSD, Major depressive episode and Burnout syndrome. This can be achieved through the detection of emotion and collection of

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Dias, A., Dias, T., Maia, E. and Praça, I.
P2DS: A Holistic Approach to Psychiatric Disease Detection in Community Pharmacies.
DOI: 10.5220/0012568200003657

In *Proceedings of the 17th International Joint Conference on Biomedical Engineering Systems and Technologies (BIOSTEC 2024) - Volume 2*, pages 768-775
ISBN: 978-989-758-688-0; ISSN: 2184-4305

physiological and performance information. All this data is then correlated using a rule-based system, grounded in the most objective medical literature, leading to the detection of the most common psychiatric diseases in pharmacists and the creation of an alert for the need to seek medical care. We expect that this system could help on early detection of psychiatric diseases, preventing health issues for community pharmacists and improving patient safety.

2 STATE OF THE ART

Health workers have a high prevalence of psychiatric diseases, especially after the COVID-19 pandemic (Braquehais & Vargas-Cáceres, 2023). According to recent literature, 100% of health workers reported Burnout and, regarding psychiatric diseases, 21,7% reported PTSD, 16,1% Anxiety and 13,3% Depression (Hill et al., 2022; Jakovljevic et al., 2021). When focusing on pharmacists, these numbers can go up to 50% for Anxiety and 44% for Depression, and about 60% for Burnout syndrome (Dee et al., 2022; Samir AlKudsi et al., 2022; Weichel et al., 2021). Among the possible causes, the high community pharmacists' workload has been a major concern (Gregório et al., 2017; Samir AlKudsi et al., 2022).

2.1 Psychiatric Diseases and Burnout

Anxiety disorders are a large group of psychiatric diseases. According to the Diagnostic and Statistical Manual of Mental Disorders (DSM-V), examples of Anxiety disorders are Generalized Anxiety Disorder, Panic Disorder and Phobias (American Psychiatric Association, 2013). Clinically, Anxiety can be experienced through psychological and physical symptoms. Psychological symptoms include fearful anticipation, which is the sensation of fear before a specific (phobia) or non-specific (generalized) event, worrying thoughts, irritability, restlessness and poor concentration. Physical symptoms can range from palpitations (tachycardia) or tachypnea to increased urinary frequency and mydriasis. Sleep disturbances, namely initial insomnia, are also common. It is defined by a Wake After Sleep Onset (WASO) or Sleep Onset Latency (SOL) superior or equal to 30 minutes, at least three nights per week (Craske et al., 2017; Harrison et al., 2017; Lichstein et al., 2003). According to DSM-V, PTSD is allocated to the stress-related disorders group. To diagnose this condition, a preceding traumatic event (witnessed or experienced) is necessary. In response to the causative trauma, the patient develops intrusive ideas (for example, re-experiencing the traumatic event or having flashbacks), leading to the avoidance of triggering stimuli, which are usually related to the traumatic event. Negative alterations in cognition and mood are present, for example amnesia, self-negative beliefs (guilt), and a negative emotional state (that includes fear or anger). Other symptoms that may be present are Anxiety-related, namely poor concentration, insomnia, and irritability. To establish a diagnosis, these symptoms must be present for over one month and cause functional impairment (American Psychiatric Association, 2013; Sareen, 2023).

Depressive disorders are characterised by depressed mood and lack of willingness and joy in activities that were once enjoyable (Harrison et al., 2017). Sadness is typically associated with Depression. However, for a depressive episode to occur, sadness must be present every day, for the most part of the day and lasting a minimum of two weeks. Other symptoms that help establishing the diagnosis are insomnia, early awakenings, fatigue, diminished efficiency, loss of weight (at least 5% body weight in 1 month) and anorexia. There are also feelings of worthlessness and guilt, which are usually excessive or inappropriate. In milder or atypical forms of the disease, symptoms that overlap with Anxiety disorders can occur, for example, irritability and hypersomnia (American Psychiatric Association, 2013; Bains & Abdijadid, 2023; Harrison et al., 2017).

Burnout syndrome is a response to chronic work stress and can be defined by emotional exhaustion, depersonalization and lack of personal achievement. Emotional exhaustion typically manifests with tiredness and fatigue, leading to increased difficulty adapting to the work environment, as the person stops having the necessary emotional energy to cope with work. Depersonalization is described as a detachment or indifference towards co-workers, sometimes leading to negative attitudes due to increased irritability. At last, people experiencing lack of personal achievement typically refer a feeling of worthlessness, of not being good enough or feeling that they are underperforming at work. Furthermore, burnout syndrome can be contagious. This phenomenon is called emotional contagion and is particularly common in health settings. It can be detected if other coworkers start experiencing the same symptoms and emotions (Edú ‑ valsania et al., 2022; Nápoles, 2022). A person with burnout syndrome expresses typical emotions that, accordingly to Otsuka et. al, are increased surprise and sadness, and decreased happiness, for more than one month. However, the authors only highlight the role of decreased happiness as a predictive factor for burnout syndrome (Otsuka et al., 2023b).

There are numerous consequences to the aforementioned diseases. In the case of Depression and Anxiety, examples include an increased risk for coronary artery disease (Ayers & de Visser, 2021). Depression alone increases the risk of type 2 Diabetes Mellitus and Parkinson disease and ultimately, if untreated, can lead to death by suicide (American Psychiatric Association, 2013; Ayers & de Visser, 2021). Furthermore, there is an increased risk for substance abuse and social isolation, leading to functional decline. In terms of work-related consequences, PTSD, Depression and Burnout lead to increased absenteeism, work-related mistakes and diminished productivity (American Psychiatric Association, 2013; Craske et al., 2017; Edú-valsania et al., 2022; Lerner et al., 2010; Vignoli et al., 2017). In conclusion, there is a growing urgency to address the emotional, physical and mental exhaustion of health workers (Mollica & Fricchione, 2021).

2.2 Related Work

In the field of psychiatric condition detection, multiple approaches have surfaced for the detection of Depression and stress, using facial expression, speech, and physiological data as the main features analysed (Saganowski et al., 2023).

Concerning PTSD, multiple works have emerged for stress detection. Grupta et. al developed a system based in the Wearable Stress and Affect Detection (WESAD) dataset, containing real-world data from corporate employees. Physiological data (ECG, temperature, respiratory rate, electrodermal activity and electromyogram) was collected through smart bands, allowing the identification of employees with abnormal levels of stress (Gupta et al., 2022). A similar approach has been used on real-word healthcare data, in an experimental fashion. Eom et. al used a dataset containing over 1000 hours of physiological data captured by an Empatica E4 band, used by hospital nurses during the COVID-19 pandemic. The nurses were also instructed to answer a stress-related survey to help validating the acquired data, which was then processed in a multimodal Convolutional Neural Network (CNN) model to predict stress. Although real-world data was used, the model was not implemented on the field (Eom et al., 2023). Muñoz and Iglesias tried a different approach, using text. They used the datasets Dreaddit, Natural Stress Emotion and TensiStrenght, which contain text data from Reddit, real world interviews and Twitter, respectively. Data was processed in a lexicon-based framework for the detection of stress (Muñoz & Iglesias, 2022). Keystroke analysis has also been used to this end by Bakkialakshmi and Sudalaimuthu. The authors collected typing data with the help of 200 volunteers which was posteriorly run through a Dynamic Cat-Boost algorithm to detect stress. (G.L. Bajaj Institute of Technology & Management, 2022). Rodrigues and Correia combined physiology and image features of 28 healthy volunteers of an insurance company. They collected heart rate and eye closure from users and validated data with stress-related questionnaires, serving as input for training machine learning models capable of predicting stress (Rodrigues & Correia, 2023). Singh et. al collected video and audio data from students using cameras and smartphone microphones, which was then run though machine learning models to detect stress (Singh et al., 2022). Lastly, Dogan and Akbulut combined physiological, audio and visual data from the WorkStress3D dataset for stress detection, by analysing facial expressions, physiological and audio data (Dogan & Akbulut, 2023). Although stress relates to PTSD, to the best of the author's knowledge, there are no systems for PTSD detection.

Concerning Depression, Francese et. al used a system that combined speech and facial recognition to increase the accuracy of the Beck Depression Inventory II (BDI-II) questionnaire, a screening tool for Depression. The combination between facial expression, speech and the answers provided in BDI-II impressed both clinicians and patients, who highlighted it as helpful in decision making (Francese & Attanasio, 2022). Yoon et al. explored the dataset D-Vlog, consisting of 160 hours of Youtube Vlog video. Speech and facial expressions were extracted, processed and combined for the detection of depression (Yoon et al., 2022). Anshul et. al tried a different approach, using text, image and account details from Twitter users. The collected data was used to train three different machine learning models to identify Depression (Anshul et al., 2023). Yang et. al used a similar methodology, retrieving Facebook data (text and account details) from the dataset "myPersonality" and Thorstad and Wolff used online text from Reddit to predict user Depression (Thorstad & Wolff, 2019; Yang et al., 2020). Park and Moon collected speech and text data from the DAIC-WOZ Dataset, which were processed separately and then fused by a multimodal fusion model to recognise Depression (Park & Moon, 2022). Chikersal et al used data from smartphones and fitness trackers to identify Depression on campus students. The collected data included number of calls, GPS location, phone usage, steps, sleep and behaviour.

Comparatively to similar works, this had the most participants and variety of devices and data sources (Chikersal et al., 2021).

Regarding Burnout, to the best of the authors knowledge, there are no detection systems that comprise wearables, facial expression, or audio. Despite this, Otsuka et. al studied the relation between emotions and Burnout by detecting the facial expression of the participants. They used a “Face Recognition and Attendance App” for facial recognition and the questionnaire BAT-J (Japanese version of the Burnout Assessment Scale) for Burnout screening (Otsuka et al., 2023a).

Table 1 encompasses the various approaches previously described. Notably, only the study by Eom et al. uses data from health workers, although the system was not tested in a healthcare setting. In contrast, Francese et al.'s work on Depression took place on a healthcare setting but targeted patients. No studies were found for the detection of a combination of diseases.

3 PSYCHIATRIC DISEASES DETECTION SYSTEM

The analysis of medical literature related to the three psychiatric diseases under analysis, PTSD, Major Depressive Episode and Burnout Syndrome, permitted the identification of the key characteristics present on each condition. We have aggregated these into three different domains: (i) human emotion, (ii) physiological signs and (iii) performance metrics. Considering the holistic setting in which these diseases can be predicted, we propose P2DS, a psychiatric diseases detection system composed of three alert-generation modules, one for each domain, and a rule-based inference engine capable of correlating the alerts generated via classification rules. Figure 1 describes a general overview of P2DS. In this architecture, the modules defined as Emotion Recognizer, Physiology Monitor and Performance Collector are constant observers of the pharmacists' emotions, physiological signs and performance metrics in the context of the pharmacy, outputting a great amount of data in real-time. The correlation

Table 1. Detection of Stress, Depression and Burnout Approaches Summary.

Author and year	**Psychiatric condition**	**Field-tested**	**Features**
(Francese & Attanasio, 2022)	Depression (aid only)	Yes	Speech + Facial recognition
(Yoon et al., 2022)	Depression	No	Speech + Facial recognition
(Anshul et al., 2023)	Depression	No	Text + Online image + Account details
(Yang et al., 2020)	Depression	No	Text + Account details
(Thorstad & Wolff, 2019)	Depression	No	Text
(Park & Moon, 2022)	Depression	No	Speech + Text
(Chikersal et al., 2021)	Depression	Yes	Physiologic signs + GPS location + calls number
(Gupta et al., 2022)	Stress	No	Physiologic signs
(Eom et al., 2023)	Stress	No	Physiologic signs + Questionnaire
(Muñoz & Iglesias, 2022)	Stress	No	Text
(G.L. Bajaj Institute of Technology & Management, 2022)	Stress	Yes	Typing patterns
(Rodrigues & Correia, 2023)	Stress	Yes	Physiologic signs + Eye closure + Questionnaire
(Singh et al., 2022)	Stress	No	Speech + Facial recognition
(Dogan & Akbulut, 2023)	Stress	No	Physiologic signs + Speech + Facial recognition
(Otsuka et al., 2023a)	Burnout	Yes	Facial recognition + Questionnaire

engine ingests this information and processes it using the classification rules defined in its knowledge base to predict the presence of psychiatric diseases, raising alerts for the need to seek medical attention. The following subsections describe in greater detail the intricacies and characteristics of each subsystem.

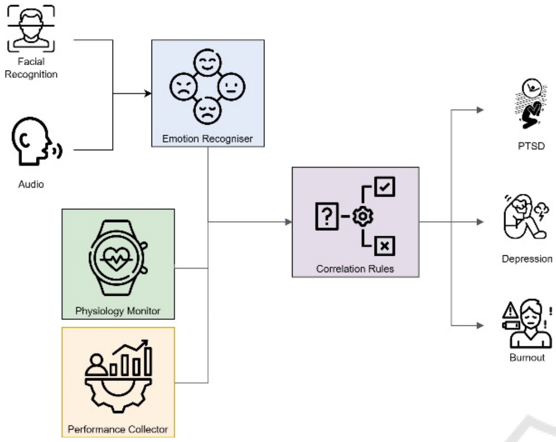

Figure 1: General overview of P2DS.

3.1 Emotion Recogniser

Emotion is a broad term that includes our affect, mood, and impulses. It is generally divided into three separate components: a cognitive one, relative to how our interpretation of a situation modulates emotion; a physiological one, related to the physiologic changes in response to emotions; and lastly a behavioural one, which includes our facial expressions (Ayers & de Visser, 2021). Technological progress has allowed the identification of human emotions through these components, with most recent approaches using Machine Learning (Cai et al., 2023; Pan et al., 2023).

The Emotion Recognizer is intended to perform emotion classification using Machine Learning models and relying on image and audio data, as these would be the expected means of communication utilized in a pharmacy. These classifiers could be trained effectively utilizing pre-existing datasets, providing that they follow Paul Ekman's model of basic emotions, a standard, cross-cultural, recognized model defining 6 universal emotions: sadness, happiness, disgust, anger, surprise and fear, plus neutral (Ayers & de Visser, 2021).

Regarding the data to train these classification models, there is a wide range of datasets for emotion detection, which have been collected in natural and induced environments. However, literature shows that models trained with data captured in a controlled environment tend to be less applicable in a real context with real conditions (Aguilera et al., 2023).

Since this module constitutes multimodality, a dataset like MELD or RECOLA would be fit for training the model (Poria et al., n.d.; Ringeval et al., 2013). Nonetheless, the importance of unimodal datasets, such as IFEED, cannot be overlooked, as these could provide valuable data to increase the model's performance and generalizability (T. Dias et al., 2023).

3.2 Physiology Monitor

The popularity of wearable health devices has increased in the recent years, as reflected by an increasing market value over the years, with more units sold (D. Dias & Cunha, 2018; Escobar-Linero et al., 2023; Lu et al., 2020). These devices allow for the continuous monitorization of a person's vital signs, providing a stream of real-time data. They have the advantage of being non-obtrusive and are readily accessible. As so, similarly to other studies cited above, the Physiology Monitor uses wearable health devices, such as smartwatches, for collecting sleep data (SOL, WASO and awakening time), cardiac and respiratory rate, tremor (via electromyogram) and sweating (via electrodermal activity).

Weight changes can be monitored by establishing the initial weight and subsequently conducting monthly re-evaluations. The use of a Bluetooth scale obviates the necessity for manual weight input. Afterwards, weight variation would be the difference between the previous and the current weight, subsequently turned into a percentage.

3.3 Performance Collector

Psychiatric diseases imply the existence of functional impairment, which may manifest by loss of performance (Telles-Correia et al., 2018). To measure this, we propose the Performance Collector, an information system designed to gather data from the software systems of pharmacies concerning the productivity, work-related errors, and absenteeism of pharmacists. The standard values for these parameters should be based on the pharmacy's estimates, as different pharmacies have different numbers of employees, sales volumes and working hours (Gregório et al., 2017). Values that are significantly different to those defined could pose a red flag for all conditions.

3.4 Correlation Engine

The Correlation Engine is a rule-based inference engine that leverages expert knowledge in the form of classification rules to perform inference. This module aggregates evidence from all three subsystems, leveraging rules to analyse the data and infer alert-raising conclusions. These rules include objective emotions, signs and other information related to each psychiatric disease.

We propose two sets of medical literature-based rules, complementary to this system, which are subdivided into main and adjuvant. The main rules include information regarding emotion. The adjuvant rules allow for a more fine-grained detection of each disease and comprise physiological and performance information. Since these are grounded on medical literature, our system achieves a greater degree of explainability in comparison to existing alternatives.

In PTSD, we defined persistent fear (for over 1 month) as a necessary condition. The adjuvant conditions are tachycardia, tachypnea, increased sweating, tremor, insomnia, increased absenteeism, work-related mistakes, diminished productivity, and irritability. As irritability is nonspecific, we considered it an adjuvant condition rather than a main one.

For Major depressive episode, daily sadness, for the most part of the day and during at least two weeks is a main condition. The adjuvants are insomnia (as defined earlier), early awakenings (compared to the normal personal awakening time), weight loss superior to 5% of total body weight in one month, increased absenteeism, work-related mistakes and diminished productivity. To cover for atypical Depression symptoms, hypersomnia (defined by delayed awakening when compared to normal) and irritability are also adjuvant conditions.

For Burnout syndrome the main condition is decreased happiness for more than one month, based on the work of Otsuka et.al (Otsuka et al., 2023a). Adjuvant conditions are increased absenteeism, work-related mistakes, diminished productivity, irritability and emotional contagion.

To increase accuracy, we propose the application of standardized score-based questionnaires, namely Primary Care PTSD Screening questionnaire (PC-PTSD-5) for PTSD, Patient Health Questionnaire-9 (PHQ-9) for Depression and Burnout Assessment Tool (BAT) for Burnout. (Bains & Abdijadid, 2023; Edú-valsania et al., 2022; Sareen, 2023; Sinval et al., 2022). Table 2 summarizes all these rules.

4 CONCLUSIONS

This article presents a novel solution for the detection of the most common psychiatric diseases in healthcare workers, particularly community pharmacists. Comparatively to other existing systems, our proposal detects three different conditions: PTSD, Major depressive episode and Burnout syndrome, which, to the best of the authors knowledge, has not been done. In addition, we designed this system to be as holistic as possible, respecting objective medical literature available, and combining image, audio, physiological and performance data. In comparison to other works that also combine multiple modalities, ours is explainable, as each correlation can be explained by the classification rules defined. In addition to the field of psychiatric disease detection, we also define, design and architect a system purposefully built to be implemented in the context of community pharmacies. Data collection in this setting is as non-obtrusive as possible, requiring only the use of a wristband, monthly weight determinations and image and audio capturing. Furthermore, this work contributes to the knowledge of psychiatric disease detection, by analysing several sources of available medical literature, using the most objective criteria possible to design the rules.

Table 2: Correlation Rules for each disease.

<table>
<tr><th>Conditions</th><th>PTSD</th><th>Major Depressive Episode</th><th>Burnout Syndrome</th></tr>
<tr><td>Main condition</td><td>Increase in fear for more than one month</td><td>Daily sadness for at least two weeks</td><td>Decreased happiness for more than one month</td></tr>
<tr><td rowspan="9">Adjuvant conditions</td><td>Tachycardia</td><td>Weight loss superior to 5% in one month</td><td rowspan="5">Emotional contagion</td></tr>
<tr><td>Tachypnea</td><td>Early awakenings</td></tr>
<tr><td>Increased sweating</td><td rowspan="3">Insomnia</td></tr>
<tr><td>Increased tremor</td></tr>
<tr><td>Insomnia</td></tr>
<tr><td colspan="3">Increased absenteeism</td></tr>
<tr><td colspan="3">Decreased productivity</td></tr>
<tr><td colspan="3">Increased work-related mistakes</td></tr>
<tr><td colspan="3">Irritability</td></tr>
<tr><td>Questionnaire</td><td>PC-PTSD-5</td><td>PHQ-9</td><td>BAT</td></tr>
</table>

ACKNOWLEDGEMENTS

This work has received funding from the project ForPharmacy (P2020-COMPETE-FEDER number 070053). This work has also received funding from projects UIDB/00760/2020 and UIDP/00760/2020.

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