Sensor-based Solutions for Mental Healthcare: A Systematic Literature Review

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Abstract: Mental well-being is a crucial aspect of the person's general health, compromised mental health impairs the person's functioning, decreases the quality of life, and limits the person's contribution to society. The mental health industry is still facing some barriers to healthcare delivery such as costs, mental health illiteracy, and stigma. Incorporating technological interventions in the treatment and the diagnosis processes might help overcome these barriers. Sensors are devices that have been used for healthcare since the 1990s and have been incorporated into mental healthcare in different forms. In this study, we conducted a systematic literature review to identify and analyze sensor-based solutions for mental healthcare. 12 studies were identified and analyzed. The majority of the selected studies presented methods and models and were empirically evaluated and showed promising accuracy results. Different types of sensors were used to collect different types of data about the patient such as physical and behavioral information. The selected studies mainly addressed the use of sensors for common mental issues like stress and depression or the analysis of general mental status. Some studies reported some limitations mainly related to technological issues and lack of standards.

1 INTRODUCTION

According to the World Health Organization (WHO), mental health is "a state of well-being in which the individual realizes his or her own abilities, can cope with the normal stresses of life, can work productively and fruitfully, and is able to make a contribution to his or her community" (Galderisi et al., 2015). Many mental disorders represent a life-long resource of dysfunction and are consistently associated with increased disability as they have a personal and socioeconomic impact (Ormel et al., 1994). Serious mental illnesses have a marked impact on life expectancy as well, which is generally higher than the impact of other well-recognized exposures such as smoking, diabetes, and obesity (Chang et al., 2011). Unfortunately, most people in need for mental care services, in both developed and developing countries, receive no services at all (Kazdin, 2019).

Many barriers to mental healthcare delivery exist, such as cost and reimbursement; policy and legal constraints; limited number of providers; stigma and self-stigma for seeking treatment; mental health illiteracy; and cultural and ethnic influences (Hinshaw and Stier, 2008; Andrade et al., 2014). Another less frequently discussed barrier, yet a very important one, is the dominant model of delivering psychosocial care, which is based on a one-to-one, in-person treatment, with a trained mental health professional, provided in clinical setting (Kazdin, 2019).

Incorporating information and communication technologies (ICT) in the treatment and diagnosis processes of mental disorders might help overcome some of the aforementioned mental healthcare delivery barriers. ICT provide several technology-enabled therapies, including internet-based programs, mobile applications and informational websites (Stone and Waldron, 2019; Drissi et al., 2019c; Drissi et al., 2019b). Sensors have been used for health purposes since the 1990s, and have been successfully used for mental healthcare purposes as well (Abdullah and Choud-

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hury, 2018; Harari et al., 2017). Their use provides different methods of data collection that can help identify the person's behaviors, physical indicators, thoughts, feelings, and traits (Mohr et al., 2017), in addition to several forms of patient's monitoring and treatment.

Researchers are showing interest in the use of sensors for mental healthcare. Among others. (Baig et al., 2017) conducted a systematic review of wearable patient monitoring systems and described challenges and opportunities. (Mukhopadhyay, 2014) reviewed sensors-based activity monitoring systems and described challenges and issues. (Drissi et al., 2019a) provided a survey of literature on the use of sensors for mental healthcare, describing addressed topics and weak areas of the research.

2 METHODOLOGY

The present study is a systematic literature review (SLR), based on guidelines proposed by (Keele, 2007), conducted on 12 studies proposing sensors-based solutions for mental healthcare. The studies selection and analysis processes are presented below.

2.1 Research Questions

Table 1 presents the research questions (RQs) of this study and their motivation.

2.2 Research Strategy

The search process started by consulting the following sources: IEEE Digital Library, ACM Digital Library, ScienceDirect, Springer Link and PubMed. The following search string was used for the automatic search of publications in the mentioned digital sources: "Sensors" AND "Mental" AND "Health" AND "Care". The search string was formulated to include a broad selection of literature. In order to determine whether to include or exclude a study, the first author conducted a primary analysis by inspecting each paper's title, abstract and keywords.

2.3 Papers Selection

After the identification of relevant publications for the study by the first author, information about each paper from the outcome of search were filled in an excel file. The second author revised the final selection. The inclusion criterion (IC) was limited to:

IC: Publications that address the use of sensors for mental healthcare.

The studies that met the following exclusion criterion (EC) were eliminated:

EC: Publications that were not solution proposals such as, opinion papers and reviews.

2.4 Data Extraction Strategy

The data extraction process was mainly centered around providing answers to the RQs. Data extracted from each selected study were:

- Type of the proposed solution, which can be classified as: models, methods, tool-based techniques or others.
- Types of sensors used in the proposed solution: how they operate and what data they collect.
- Types of data collected by the sensors.
- Limitation of the proposed solution.
- Whether the proposed solution has been empirically evaluated and how. An empirical evaluation method can be classified as: experiment, case study, survey, interview, or other.
- Mental disorders and mental health related issues addressed by the selected solution proposals.

3 RESULTS

12 studies were selected as shown in Figure 1. Results from the papers selection and data extraction processes are presented in Table 2.

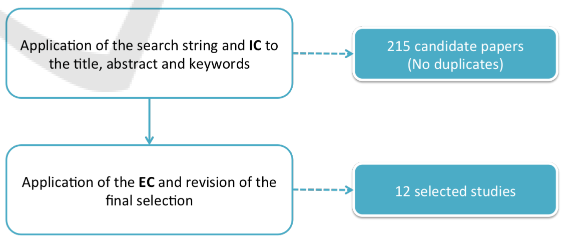

Figure 1: Selection process.

3.1 RQ1. Types of the Proposed Solutions (Contribution Types)

The contributions of the papers were mainly methods and models with 41,67% each, and 16.66% tool-based techniques. This section describes each solution and how sensors were used in it.

(Yamaguchi et al., 1998) developed an indoor monitoring system based on infrared positioning sensors and magnetic sensors to observe the person's be-

Table 1: Research questions and their motivations.

ID	Research Question	Motivation
RQ1	What is the type of the proposed solution ?	To identify the different contribution types of the selected papers
RQ2	What are the types of sensors used in the proposed solutions ?	To identify the different types of sensors and the most used ones for mental healthcare purposes
RQ3	What are the types of data collected by the sensors ?	To identify the different types of data that could be collected by sensors and used for mental health care
RQ4	What are the limitations of the proposed solutions ?	To identify problems and limitations associated with the use of sensors for mental healthcare
RQ5	Are the proposed solutions empirically validated or evaluated ?	To discover whether the efficiency of a proposed solution has been empirically validated or evaluated
RQ6	What are the most addressed mental disorders and mental health related issues in publications proposing sensors-based solutions for mental illnesses ?	To identify mental issues and disorders that are likely to be managed with sensors-based solutions

Table 2: Results. *Acronyms: Electroencephalography (EEG), Electrooculography (EOG), Electrocardiogram (ECG), Galvanic Skin Response (GSR), Global Positioning System (GPS), Heart Rate (HR), Short Message Service (SMS).*

Ref.	Year	RQ1	RQ2	RQ3	RQ5	RQ6
(McGinnis et al., 2018)	2018	Method	Belt-worn sensor	Motion: acceleration and angular velocity	Experiment	Depression, anxiety
(Sahu and Sharma, 2016)	2016	Model	EEG and EOG sensors	Brainwaves and eye movement	No	General mental status
(Farhan et al., 2016)	2016	Method	Smartphone sensors	Physical Activity, light information, conversations, phone lock, GPS location, audio	Experiment	Depression
(Sano et al., 2015)	2015	Method	Wrist sensor	Skin temperature, skin conductance, activity, light exposure, call, SMS, location, internet usage and "screen on" timing	Experiment	General mental status, sleep quality
(Sandulescu et al., 2015)	2015	Method	Wristband sensor	Electro-dermal activity, pulse plethysmograph and blood volume	Experiment	Stress
(Palmius et al., 2014)	2014	Model	Wrist sensor and smartphone sensors	Activity, sleep, ambient light levels and social network activity	Experiment	General mental status
(Sano and Picard, 2013)	2013	Tool-based technique	Wrist sensor	Acceleration information and skin conductance	Experiment	Stress
(Burns et al., 2011)	2011	Model	Smartphone sensors	GPS location, ambient light, recent calls, SMS, emails	Experiment	Depression
(Wijsman et al., 2011)	2011	Method	Wireless chest belt, piezoelectric film sensor, wireless hand sensor and commercial gel electrodes	Electrocardiography, respiration, skin conductance, and electromyography signals	Experiment	Stress
(Fletcher et al., 2010)	2010	Tool-based technique	Electrodermal activity sensors, mobile Photoplethysmography sensors	Skin conductance, blood volume pulse, HR	No	General mental status
(Sun et al., 2010)	2010	Model	ECG sensor, chest strap, GSR sensor, accelerometer	HR variability, GSR and movement	Experiment	Stress
(Yamaguchi et al., 1998)	1998	Model	Infrared positioning sensors and magnetic sensors	Activity and behavior (use of rooms, equipment, bed. etc)	Experiment	Behavior

havior and activity. Results showed that it is possible to learn and measure a person's behavior, which can be used for behavioral prediction if analyzed correctly. (Sun et al., 2010) presented an activity-aware mental stress detection system, where physiological measures like heart rate variability, galvanic skin response (GSR) and movement data were collected during three physical activities (sitting, standing, and walking) using an Electrocardiogram (ECG) sensor, a chest strap, a GSR sensor, and an accelerometer. Collected data was analyzed and classified using machine learning features to detect stress. The system achieved a classification accuracy of 80%.

(Fletcher et al., 2010) described a list of different types of sensors and wireless solutions, and presented a list of opportunities and challenges associated with the use of these technologies. (Wijsman et al., 2011) presented an approach to detect stress

Table 3: Categories of the used sensors. *Acronyms: Electroencephalography (EEG), Electrooculography (EOG), Electrocardiogram (ECG), Galvanic Skin Response (GSR).*

Ref	**Category**	**Sensors**
(McGinnis et al., 2018; Sahu and Sharma, 2016; Sano et al., 2015; Sandulescu et al., 2015; Palmius et al., 2014; Sano and Picard, 2013; Wijsman et al., 2011; Fletcher et al., 2010; Sun et al., 2010)	Sensors attached to the users body	EEG, ECG and EOG sensors, belt-worn sensors, wrist sensors, chest straps, piezoelectric film sensors, wireless hand sensors, commercial gel electrodes, electrodermal Activity sensors, accelerometers, and GSR sensors
(Farhan et al., 2016; Sano et al., 2015; Palmius et al., 2014; Sano and Picard, 2013; Burns et al., 2011; Yamaguchi et al., 1998)	Sensors attached to objects used by the user or objects surrounding the user	Built-in smartphone sensors, positioning sensors, and magnetic sensors

using physiological indicators. Different physiological signals were measured using different sensors, an analysis of the collected data resulted in a set of 7 principal components that could be used for stress detection. The study showed a classification accuracy of 80% between stress and non-stress conditions.

(Burns et al., 2011) studied the feasibility and effectiveness of a mobile phone- and Internet-based intervention for depression sufferers (Mobilyze!). The study yielded an accuracy of (60% to 91%) predicting categorical contextual states (e.g., location) and a poor predictive capability for states rated on scales (e.g., mood). The study also showed the potential efficacy of these types of interventions and described a list of lessons learned and limitations of the approach.

(Sano and Picard, 2013) presented a tool-based technique aiming to find physiological or behavioral markers for stress, the technique is based on data about the patient's acceleration information and skin conductance collected from a wrist-worn sensor, surveys, and mobile phone usage. Correlation analysis of the collected data showed over 75% accuracy of low and high perceived stress recognition.

(Palmius et al., 2014) proposed a smartphone-based system that allows the remote realtime collection of data about psychiatric patient symptoms to enable efficient allocation of psychiatric resources. The data collection process is based on a wrist-worn activity and sleep tracker and an Android-based mobile application.

(Sano et al., 2015) proposed an approach to determine academic performance, sleep quality and mental health conditions based on data collected from wearable wrist sensors like skin conductance, activity and light exposure, as well as data on smartphone usage such as calls, SMS and "screen on" timing. Collected data was then analyzed using feature selection and machine learning techniques. The evaluation process yielded classification accuracies that ranged from 67 to 92% between the method and self-filed tests by participants.

(Sandulescu et al., 2015) presented a machine learning approach for stress detection using wearable physiological sensors. Physiological data were collected using a wristband sensor then analyzed using machine learning techniques to classify the state of a patient into "stressful" or "non-stressful" situations. Classification results were found to be 73% to 83% accurate.

(Farhan et al., 2016) introduced an approach to find behavioral features that are correlated with depression. The approach is based on smartphone data collection to collect information about the patient such as physical activity, light information, conversation, phone lock and GPS location, with the help of built-in smartphone sensors, then applies a multi-view bi-clustering algorithm to identify homogeneous behavioral groups. A validation process of the approach yielded an accuracy of 87%.

(Sahu and Sharma, 2016) presented a system that collects certain parameters of brainwaves and eye movement then interprets them using signal processing modules to determine the mental status of the patient. Results can be displayed, used to initiate a message alerts or feed the data to other systems.

(McGinnis et al., 2018) proposed a new approach of diagnosing depression and anxiety in young children, by the use of a 90-seconds fear induction task during which the child movement is monitored using a commercially available belt-worn sensor coupled with machine learning. The method has been empirically evaluated by an experiment that showed an accuracy that can reach 75%.

3.2 RQ2. Types of Sensors used in the Proposed Solutions

Table 3 presents the different types of sensors used in each solution. Two different categories of sensors were identified: sensors that operate by being attached to the user's body and sensors that are either attached to objects used by or surrounding the user. Some studies used more than one type of sensors.

Table 4: Categories of the collected data. *Acronyms: Galvanic Skin Response (GSR), Global Positioning System (GPS), Heart Rate (HR), Short Message Service (SMS).*

Ref	Category	Data
(Sahu and Sharma, 2016; Sano et al., 2015; Sandulescu et al., 2015; Sano and Picard, 2013; Wijsman et al., 2011; Fletcher et al., 2010; Sun et al., 2010)	Physical information	Brainwaves, eye movement, skin temperature, skin conductance, electrodermal activity, pulse plethysmography, blood volume, sleep, electrocardiography, respiration, HR, GSR and electromyography signals
(McGinnis et al., 2018; Farhan et al., 2016; Sano et al., 2015; Palmius et al., 2014; Sano and Picard, 2013; Sun et al., 2010; Yamaguchi et al., 1998)	Activity and behavior	Acceleration, angular velocity, physical Activity, movement, sleep and behavior
(Farhan et al., 2016; Sano et al., 2015; Palmius et al., 2014; Sano and Picard, 2013; Burns et al., 2011)	Smartphone usage	Ambient light, phone Lock, GPS Location, audio, calls, SMS, emails, internet usage and "screen on" timing

3.3 RQ3. Data Collected by the Sensors

We identified three categories of the collected data: physical information, activity and behavior, and smartphone usage as presented in Table 4. Some solutions used more than one category of data. Table 2 shows data used in each solution.

3.4 RQ4. Limitations of the Proposed Solutions

Only 5 out of the 12 selected studies reported some limitations to their solutions. A number of the selected studies reported some similar limitations, like connectivity problems, power consumption issues, amount and accuracy of the collected data, and accurate analysis and interpretation of the data (Burns et al., 2011; Wijsman et al., 2011; Fletcher et al., 2010; Sun et al., 2010). When using positioning and magnetic sensors for activity and behavior sensing, some limitations were reported such as the limited functioning of the sensors under some external environmental factors like hot air, and the inability to distinguish data in case of multiple users, which makes the system helpful only in case of monitoring one patient (Yamaguchi et al., 1998). Adaptability limitations and lack of standards were also reported (Burns et al., 2011; Fletcher et al., 2010).

3.5 RQ5. Empirical Evaluation of the Solutions

The majority of the selected solutions (83%) were empirically evaluated by experiments, only 17% (Sahu and Sharma, 2016; Fletcher et al., 2010) were not empirically evaluated and classified as theories.

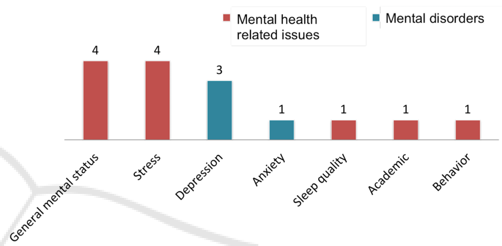

Figure 2: Addressed mental disorders and mental health related issues in the proposed solutions.

3.6 RQ6. Addressed Mental Disorders and Mental Health Related Issues

Stress is the most addressed issue by the selected solutions and depression is the most addressed disorder. Many studies did not address a specific mental disorder and proposed solutions to predict the general mental status of the user. Other studies used sensors to observe indicators of the sanity and mental status of the user such as behavior, academic performance, and sleep quality. Figure 2 presents all the addressed mental disorders and mental health related issues.

4 DISCUSSION

4.1 Types of the Proposed Solutions

The selected studies were not limited to providing IT-related solutions on the use of sensors, but also provided new psychotherapy-related approaches for the diagnosis, treatment, and monitoring of mental disorders that are only possible by the use of sensors such as associating behavioral traits with the mental status (Farhan et al., 2016; Yamaguchi et al., 1998), predicting mental status by analyzing use of smartphones (Sano and Picard, 2013; Sano et al., 2015) and detection and diagnosis of mental illnesses based on physiological indicators (Sandulescu et al., 2015; Wijsman et al., 2011; Sahu and Sharma, 2016). The use of sensors in mental healthcare has opened a new window of opportunities not only in creating new systems and technologies but also in creating new approaches and methods for the diagnosis and treatment of mental disorders. A need for publications proposing guidelines and recommendations on the use of sensors for mental healthcare has been identified, which is necessary to prevent errors and create effective solutions.

4.2 Sensors Types

Sensors were incorporated in different ways in the selected solutions, depending on the type, sensors were used to collect data from the patient's body and environment, and to detect habits and behaviors. Sensors are convenient devices that can easily be attached to the body, or objects from the environment, and that are already integrated into devices like smartphones and computers. The variety in the types of sensors helped detect different indicators and gather different types of information that are helpful in the diagnosis and management of mental illnesses, and also encouraged researchers to find associations between different types of data and mental status.

4.3 Data Collected by the Sensors

The selected solutions used sensors mainly to collect and detect three categories of data: *physical information*, *activity and behavior*, and *smartphone usage*.

- Patterns of physical symptoms are associated with certain mental illnesses, therefore can be used to detect psychological disorders (Larson et al., 2001).
- Activity and behavior were found to have a bidirectional connection with mental disorders, as regular physical activity have an inverse association with depression and anxiety symptoms (King et al., 2013), also physical activity is associated with reduced risk of some mental disorders and reduced degree of co-morbidity (Ströhle et al., 2007) and may be used as a safe and cost-effective prevention and treatment tool (King et al., 2013), analyzing activity and behavior can create an understanding of the mental status of the person. On the other hand, some mental barriers like fear were proved to have a negative impact on the person's physical activity and social behavior (Stafford et al., 2007), changing bad behaviors and improving physical activity can improve the mental status.
- Analyzing smartphone usage habits can provide an initial view of the mental status of the person. Compulsive usage of smartphones is related to some psychological traits like anxiety (Lee et al., 2014), self-control and communication issues, and general mental discomfort (Jang and Kwag, 2015).

4.4 Limitations of the Proposed Solutions

The use of sensors for mental healthcare offers many opportunities, yet it faces some limitations that need to be addressed to benefit effectively from the sensors technology. Most of the reported limitations were related to technological issues which are relatively straightforward to fix once recognized, either by using a different technology or approach. Technological issues are common and are usually overcome due to the continuous technological development. Lack of standards was also among the reported limitations, which needs to be addressed by standardization organizations, as standards and guidelines are crucial to the making and success of the solutions, more research and solutions are needed in this area.

4.5 Empirical Evaluation

The only identified empirical evaluation method in the selected studies was experiments, which was adopted mainly for the controlled conditions and environment. All empirically evaluated solutions followed similar processes and had the main necessary elements of experiments (Jedlitschka and Pfahl, 2005). The empirical evaluation of the sensors-based solutions yielded promising accuracy results, with a maximum reported accuracy level of 92% (Sano et al., 2015). But the controlled environment of experiments raises some concerns, as most of the proposed solutions are supposed to be used by the patients in real and not controlled circumstances, that differ from a patient to another and from an environment to another, which might affect the reported accuracy.

The use of other empirical evaluation methods can be beneficial and help improve the proposed solutions, for example, case studies can help detect possible issues and barriers of implementing the solutions in real life, surveys can help gather needed data, and interviews can be used to identify and understand patients' and clinicians' opinion on the solutions, which is crucial and taking it into consideration may result in more effective solutions.

4.6 Addressed Mental Disorders and Mental Health Related Issues

Depression and stress were proved to have an association with physical indicators like heart rate and physical activity (King et al., 2013), which makes sensors a helpful tool to manage these types of disorders and issues, as sensors are mainly used to measure physical indicators and observe activity and behavior. The selected solutions do not address complex disorders such as schizophrenia, bipolar disorder or psychosis, which might be due to the complex nature of these disorders and the unwillingness or inability of patients with these types of mental illnesses to use sensors-based treatments. The use of sensors in mental healthcare creates new ways of diagnosis, treatment, and monitoring. Future studies should address the use of sensors for different types of mental disorders.

4.7 Limitations

This study may have some limitations, such as: (i) missing terms from the search string might have implications on the results; and (ii) other RQs might have been relevant to extract further information from the selected studies.

5 CONCLUSION

Sensors have been incorporated in mental healthcare for several purposes, sensors can be used to monitor the physical activity and behavior, measure physical indicators or collect daily habits and information about the person. In this paper, we identified and analyzed 12 sensors-based solutions for mental healthcare. Different types of sensors were used in the solutions, to collect and manage different types of information about the patients. The majority of the solutions were designed to monitor stress, depression and general mental status, and were empirically evaluated and showed promising results.

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