# MiCare: An IoT-Based System for Real-Time Mental Health Monitoring and Early Disease Detection

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## Abstract

Mental health disorders, particularly among young adults, are a growing concern, requiring innovative solutions for effective diagnosis and treatment, based on a solid data management. *MiCare*, an AI-driven technological platform, aims to revolutionise mental healthcare through personalised patient care management, continuous remote monitoring, and early detection of abnormalities. Integrating wearable devices, patient records, and electronic health records, the platform features a Bayesian Network-based Clinical Decision Support System (Clinical Decision Support System (CDSS)) that leverages heterogeneous data to assist healthcare professionals with data-driven insights while ensuring transparency, explainability, and responsible data management. A centralised *Signal Processing* component processes physiological signals such as Photoplethysmographic (PPG) and Galvanic Skin Response (GSR), transforming real-time sensor data into features that serve as digital mental health biomarkers. These are combined with psychodiagnostic tools and patient diaries collected through the *Mobile App*, as well as clinician inputs via the *Dashboard*, constituting a comprehensive database for personalised therapeutic support. Key innovations include broader coverage of mental health disorders, integration of physiological data with traditional psychological measures, and predictive analytics for early intervention. *MiCare* supports remote, cost-effective therapy, empowering clinicians with actionable insights also via informative data visualisations, and patients with an engaging, gamified approach.

This paper highlights *MiCare* 's potential to enhance mental health diagnosis, monitoring, and treatment, leveraging data integration to foster a paradigm shift towards data-driven, patient-centred mental healthcare.

## Keywords

Continuous Health Monitoring, Decision Support Systems, Early Disease Detection, IoT System, Mental Health, Physiological Data, Remote Monitoring



## 1. Introduction

Digital technology, intended here as the application of digital technologies in healthcare [1], can account for the monitoring, treatment and even the prevention phases of a disease in a remote modality, bringing invaluable advantages to a person's health. Such a digital modality requires and, at the same time, has as outcome an enormous amount of actionable, clinically-relevant data, which are collected through but can also be leveraged by the health monitoring solutions. In fact, by integrating within them Machine Learning (ML) systems, these data can be exploited to deliver meaningful insights and data-driven "personalised" services. In addition to this, Digital Decision Support System (DSS), intended as "computer-based systems that bring together information from a variety of sources, assist in the organisation and analysis of information and facilitate the evaluation of assumptions underlying the use of specific models" [2] can provide new opportunities for digital phenotyping [3] and remote intervention, further assisting clinicians in making sense of data. In order to have these opportunities comprehensively implemented, an adequate data management system is required to handle all data revolving around digital technologies and allow for effective data integration, data mining, and data visualisation at successive stages, while ensuring privacy, security and responsible data management.

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Considering the described framework, this paper introduces *MiCare*, an integrated system to support the patient's and clinician's handling of mental health interventions by means of efficient data management and Artifical Intelligence (AI) applications. These include a DSS that integrates wearable sensor data to the other employed data sources and exploits a Bayesian Network (BN) model to provide therapeutic suggestions and insights to mental health experts, and a chatbot, which provides patients with real-time and personalised psychological and therapeutical assistance. *MiCare* proposes the complete digitalisation of the therapeutic process throughout a system based on six interconnected components: the *Dashboard*, the *Mobile App*, the *Chat*, a CDSS, a *Signal Processing* component, and an *Authenticator*. The paper illustrates the components and architecture of *MiCare*, stressing how these guarantee an optimised, efficient and, ultimately, user-friendly solution in the management of the therapeutic process, which both the patients and clinicians can benefit from. Moreover, it underlines its potential in delivering continuous, timely and personalised support thanks to the integration of AI solutions that, leveraging Large Language Models (LLMs) and electrophysiological signal analysis, can provide real-time and remote warning of at-risk situations, as well as recommendations and feedback to both the *MiCare* recipients. Such a system, designed to favour the acquisition and processing of heterogeneous mental health-related data, which span from physiological signals from wearable devices to traditional psychological assessments, make *MiCare* a valuable tool in the landscape of mental health digital technologies for continuous monitoring and early disease detection.

The paper is structured as follows: Section 2 summarises the use of wearable sensors for continuous health monitoring and prevention, especially focusing on the current research on DSS and physiological data analysis in the context of mental health; Section 3 describes *MiCare* and its architecture in detail, displaying the functionalities and interconnection among all its components; finally, Section 4 stresses the contribution of *MiCare* as a multichannel system that enhances remote mental health monitoring and early disease detection leveraging heterogeneous data.

## 2. Background and motivation

This section gives a brief overview of the Digital Mental Health Interventions (DMHIs) available in the market and of the main topics and innovation areas that the *MiCare* platform covers with the functionalities it provides. The discussion includes (i) the employment of wearable sensors for remote health monitoring and early disease detection, with a focus on the physiological data analysis, and (ii) the use of DSS for mental health assessment.

### 2.1. Overview of available digital mental health platforms

Most of current applications of DMHIs, irrespective of the integration of Decision Support Systems (DSSs) or wearable sensor data, either serve as multimodal internet- and mobile-based psychotherapy service providers [4] such as BetterHelp[1] or, in the Italian landscape, Serenis[2] and Unobravo[3], or they focus on a limited subset of psychiatric disorders, being therefore specifically addressed to patients suffering from a single mental disease. These include depression [5, 6], psychosis [7, 8], or both anxiety and depression [9]. In addition, most applications discard a comprehensive management of the therapeutic process, as this should be handled by both expert clinicians and patients in all respects.

However, few platforms [10, 11, 12], including GRETA[4] in the Italian scenario, stand out as they all provide structured data collection, customisable assessments, real-time symptom tracking also via interactive visualisations, and both mobile [13] and web applications to support clinicians and patients. Moreover, they allow the administration of automated surveys, cognitive tasks, and self-reported psychometric measures for continuous symptom monitoring. Greta focuses on psychotherapy, supporting documentation management, homework assignments, and structured progress tracking. As

[1] www.betterhelp.com
[2] wwww.serenis.it
[3] www.unobravo.com
[4] www.greta.digital

mindLAMP[5], it emphasises clinician-patient communication, offering chat functionalities to maintain engagement between sessions. LAMP platform and Innowell platform further integrate behavioral and physiological data collection from third-party sources, such as wearable sensors, with MindLAMP Cortex toolkit offering advanced data analytics. Finally, MindLogger[6] and MindLAMP notably contribute to clinical research, offering open and customisable architectures.

### 2.2. Wearable sensors and physiological signals for mental health monitoring and early disease detection

The term "health monitoring" typically refers to the technologies developed and used to monitor biosignals [14]. Especially after the pervasive widespread of mobile devices, it is via wearable sensors that individuals' health is being tracked [15]. Not only they have applications in sports and fitness, wellness and lifestyle, and military and industrial settings [16], but they are also being used to address major challenges in the medical field, such as diabetes management, hypertension and cardiovascular diseases [17], or remote monitoring of the elderly [18, 19] suffering from chronic diseases [20]. Wearable sensors can be leveraged to collect sensor data, that is, passive data that can be automatically recorded via smartphone or wearable devices and that can measure physiological signals. These signals are generated by the Autonomic Nervous System (ANS) and, since its activation is mainly involuntary and cannot be controlled, they can be monitored in a continuous way over time to detect changes that can be associated with the occurrence (and, eventually, persistence) of disorders related to mental health. Examples of physiological signals are the PPG signal, which detects volumetric variations of blood circulation in tissues and is an alternative to Electrocardiography (ECG) to estimate Heart Rate Variability (HRV), and the GSR, which is a continuous measurement of human skin conductance. Changes in skin conductance correlate with the self-reported evaluation of arousal [21], suggesting that GSR can indicate a subject's emotional [22] and cognitive activity. PPG and GSR signals can be specifically collected via wearable commercial wristbands, such as the Empatica[7], Garmin[8], and FitBit[9]. It is reported [23] that most of wearable-based eHealth (electronic-Health) data is currently obtained from sensors such as accelerometer, gyroscopes, electrocardiogram, electroencephalogram (EEG), and blood glucose sensors. Reducing the burden associated with active data collection, sensor data constitute novel digital markers of behaviour [24] to be associated with questionnaires and self-tracked lifestyle data.

While many studies employed wearable devices collecting physiological signals in the broader domain of eHealth to promote physical activity and monitor more general mental-related issues [25], there is limited research on their utilisation in the psychological field, both in terms of quantity and validation discussion. PPG data was integrated into some preliminary psychiatric eHealth studies, including the one proposed by [26] to detect worsening of suicidality in adolescents, and the investigation by [27] to assess whether a PPG-based analysis could predict Post-Traumatic Stress Disorder (PTSD) outcomes (*e.g.*, sleep anxiety, pain). Even sensor data collected via smartphones rather than via wearable devices, such as physical activity, geolocation, phone unlock duration, and speech frequency and duration, proved to be indicative in predicting a relapse for patients suffering from psychosis [28]. Some studies combined wristband and smartphone sensors data to monitor changes in depression severity [29].

### 2.3. Decision support systems for digital mental health technologies

The increasing availability of health-related data mainly collected through Digital Health Technologies (DHTs) presents a significant opportunity for transforming raw data into actionable insights and DSSs could provide valuable insights into diagnosing and monitoring mental health disorders. However,

[5] www.docs.lamp.digital
[6] www.mindlogger.org
[7] www.empatica.com
[8] www.garmin.com/it-IT/c/wearables-smartwatches
[9] www.store.google.com/it/category/trackers

a significant limitation in this context lies in the fact that the field of mental health currently lacks validated technical tools and biomarkers for decision-making [30], which often results in treatment decisions and diagnoses based on self-reported measures and clinical interviews only [31], without any quantitative physiological sensor data being involved.

Leveraging a framework [32] based on a thematic analysis [33] conducted to identify the components of DSSs in healthcare, we discuss some state-of-the-art (SOTA) works on the use of DSSs in the specific domain of psychiatry according to five dimensions: used data, technology employed for data collection and decision making, involved disease, and decision type (*e.g.*, diagnosis, monitoring). Based on a review conducted by [30], sensor data have a limited use within DSSs, mostly leveraging questionnaire results, medical records and sociodemographic data. ML models are still predominant compared to deep neural network approaches for building DSSs. This is likely due to the lack of explainability of the results produced by the latter, which contrasts with the intrinsic need to provide interpretable insights to support mental health professionals in the meaning-making of the therapeutic process. Implemented models also included Bayesian models, such as the one proposed by [34] . Many works focused on the study and prediction of PTSD [35, 36, 37], but DSSs focusing on a combination of other psychiatric issues and related decision tasks, such as prevention of suicide attempts [38], depression, drug repositioning for anxiety [39], and identification of schizophrenic episodes [40] can also be found.

Regarding the use of wearable sensor data within DSS in the mental health field, limited but promising studies can be found in the literature. The use of physiological data within a DSS could provide significant information to support clinical management of long-term mental conditions, including anxiety, bipolar, psychotic, and eating disorders, as well as major depression [41], constituting digital biomarkers of mental issues symptoms. Despite this potential, it is reported that only one percent of marketplace apps dedicated to mental health supports the use of sensors [42], suggesting that the "concepts of digital phenotyping to support just-in-time adaptive intervention (JITAI) or behavioural interventions via apps are largely not incorporated into existing commercial technologies" [24].

Provided this overview, we propose our instance of a system to support real-time remote health monitoring and early disease detection in the broad mental health field. The system integrates a CDSS, leveraging heterogeneous data sources that include traditional psychological data as well as passively and continuously recorded physiological signals. Moreover, it is designed to be utilised by both patients and mental health experts, the latter having at disposal data visualisations for monitoring their patients' progress over time.

## 3. MiCare and its architecture

*MiCare* is a technological solution that digitalises the entirety of the therapeutic processes for patients within the mental health field, particularly for those suffering from personality, eating, anxiety and psychotic disorders, as well as depression. The *MiCare* system is based on six interconnected components (Fig. 1): (i) the *Dashboard*, a web browser accessible platform dedicated to clinicians and suited for managing the entire patients' therapeutic process, (ii) the *Mobile App*, designed to assist patients with mental health difficulties and that features Gamification and Token Economy strategies, (iii) the *Chat*, devised for personalised support to therapists during decision-making and to patients while the therapist is not present, (iv) the CDSS, utilising data from the *Dashboard*, the *Mobile App*, and wearable sensors to provide decision support to the clinician, (v) the *Signal Processing*, that prepares physiological signals obtained via wristbands that contain wearable sensors for the CDSS, and (vi) the *Authenticator*, that manages authentication to access the *Dashboard* and the *Mobile App*.

The *MiCare* platform requirements were gathered via two modalities: market and SOTA analysis, as discussed in Section 2, and collaboration with various organisations, hospitals, stakeholders from different healthcare sectors, and specialised training schools. These organisations are currently using the MiCare system, with the aim of gathering additional user requirements and validating its functionalities. Initial results show good adoption, with a high level of acceptance from both patients and professionals and a general improvement of remote monitoring and effectiveness of clinical decision-making. Addi-

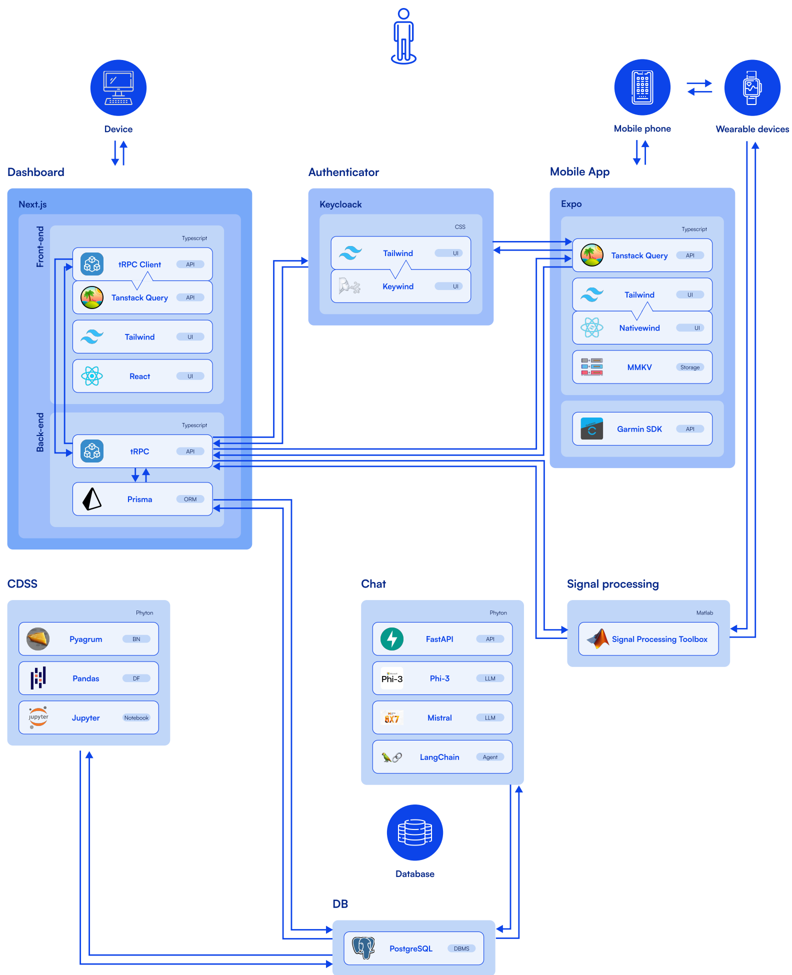


**Figure 1:** Complete architecture of the proposed *MiCare* platform.

tionally, the analysis of collected data is contributing to the refinement of the predictive model and the optimization of intervention strategies.

All data used on *MiCare* are either collected via the system itself or directly uploaded to one of its components by clinicians or other professionals utilising the platform. Successively, they are stored into a PostgreSQL database, where they are queried from whenever required. The only external data source is constituted by the Garmin vívosmart® 5 wristbands[10], which are commercial fitness trackers equipped with wearable sensors and that are chosen to be provided to patients involved in the use of *MiCare* to acquire their physiological data. As explained in more detail into the following subsections, the other type of data shared across *MiCare* is constituted by electronic health records, digitised medical records, filled-in monitoring forms, psychological tests results and patients diaries, resulting both in structured and unstructured (mainly textual) data.

Privacy, security, and trust management are core elements of *MiCare*. Informed consent is required to patients for being inserted into the platform and for using the *Mobile App*, to make them aware transparently of how their data are collected, used and shared, in line with the principles of transparency and accountability promoted by the AI Act[11]. *MiCare* complies with data privacy regulations, such as the GDPR[12], ensuring maximum protection of patient information. Moreover, the platform will

[10] www.garmin.com/it-IT/p/782585
[11] www.europarl.europa.eu/topics/en/article/20230601STO93804/eu-ai-act-first-regulation-on-artificial-intelligence
[12] www.garanteprivacy.it/regolamentoue

integrate the FHIR (Fast Healthcare Interoperability Resource) standard[13], which enables secure and standardised exchange of healthcare information between the different components of the platform. This is essential to facilitate interoperability of the different kinds of data managed across *MiCare*, ensuring a consistent flow of data, and guaranteeing the future possibility of integration with other healthcare systems to facilitate clinical information access and sharing among various stakeholders.

In the following subsections, the functionalities of all the components and the modalities through which they are interconnected are explained.

### 3.1. Dashboard

The ***Dashboard***[14] (Fig. 2) is a web-based platform specifically designed to support mental health professionals in their practice, accounting in an efficient way for several aspects regarding daily patients management. Its digital environment addresses multiple functionalities, mainly involving patient data management and treatment effectiveness analysis. Particularly, the tasks handled by the *Dashboard* are the following:

- possibility of managing patient medical records, from the upload of new documents, which may eventually be digitised via automatic handwriting extraction [43], to the compiling of pre-structured digital forms, and finally the visualisation, which provides a more intuitive evaluation of the effectiveness of interventions. This way, clinicians can monitor patients' progress and adjust therapeutic strategies based on the collected data;
- administration to patient of psychological tests, which are compiled via the *Mobile App*, and consultation of their results, whose data can be visualised within the *Dashboard* and are automatically integrated into the CDSS. Psychological tests are included into the *Dashboard* as a library of digitised questionnaires. Examples of the included questionnaires are the Patient Health Questionnaire 9 [44], used to quantify depression, and the Generalized Anxiety Disorder 7 [45], which measures anxiety [46];
- calendar feature, for scheduling patients' appointments;
- creation of new users in the *Mobile App* within Keycloak[15], an Open Source IAM solution supported by RedHat;
- possibility of chatting with the *Chat* to receive support in daily patients monitoring as well as in clinical decision-making, with suggestions provided based on the CDSS.

Each patient has its own clinical folder, where the therapist uploads and eventually modifies or deletes related data. The *Dashboard* component takes as input data about patients which are of various nature and are obtained through multiple modalities: they can be digital or automatically digitised medical records uploaded by therapists, diaries and psychological assessment results received from the *Mobile App*, digital medical forms filled in by the therapist, or, finally, aggregated physiological data from wearable sensors. All these data are queried from the database where they are stored whenever the therapist decides to consult or visualise them. The same kind of data are produced as output and written again (if they had been changed) in the database. They are successively exploited by the *Mobile App*, the *Chat*, and the *CDSS* for the purposes that will be explained in the respective subsections. Finally, the calendar feature communicates with the *Mobile App* used by the patients.

The *Dashboard* was engineered using **Next.js**[16], the most widespread full-stack JavaScript **React** based framework, with **TypeScript**[17] for type safety. The back-end of the dashboard leverages **tRPC**[18] to streamline middleware handling for all the communication that occurs in the *MiCare* ecosystem, in

[13] www.hl7.org/fhir
[14] www.github.com/unimib-datAI/micare-dashboard
[15] www.keycloak.org
[16] www.nextjs.org
[17] www.typescriptlang.org
[18] www.trpc.io

conjunction with Next-Auth[19] for session management. **Prisma**[20] is employed as Object Relational Mapper (ORM) to facilitate database querying and schema management. As such, Prisma allows to easily write data inside the chosen PostgreSQL[21] database. For front-end styling, **Tailwind CSS**[22] accelerates component design, whereas **TanStack Query**[23] efficiently manages data fetching by interfacing with tRPC client functions. Authentication and authorisation to access the *Dashboard* are explained in Section 3.6.

In addition to these functionalities, the *Dashboard* is planned to include a section dedicated to research, where aggregated and anonymised data utilised within the *MiCare* ecosystem can be made available to the scientific community at the national level. This would enable the collection, monitoring, and analysis of psychological and psychotherapeutic treatments by experts who could leverage this abundance of data to advance scientific knowledge in the clinical field.

The *Dashboard* represents a tool that mental health professionals, including psychiatrists, psychologists, and psychotherapists, can effectively benefit from for a comprehensive patient assessment. By providing the possibility of continuously and remotely monitoring patients' physiological signals, of administering and evaluating psychological tests, and finally chatting with an AI-powered chatbot that may even send alerts in case of at risk situations, the *Dashboard* facilitates early intervention, and promotes better long-term management of mental issues.

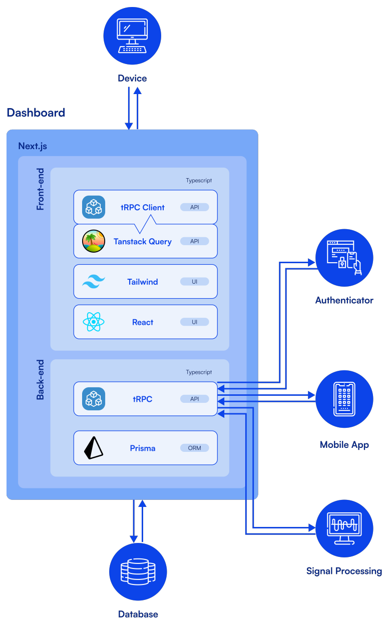


**Figure 2:** Architecture of the *Dashboard*.

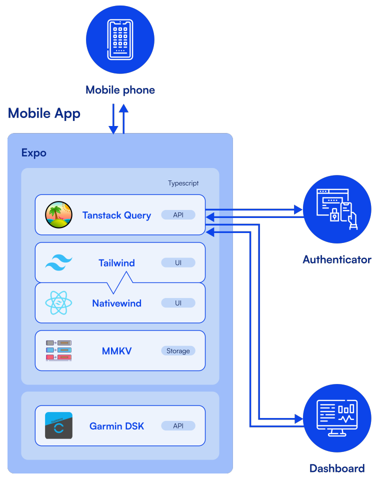


**Figure 3:** Architecture of the *Mobile App*.

## 3.2. Mobile app

In contrast with the *Dashboard*, which is addressed to clinicians, the ***Mobile App***[24] (Fig. 3) is developed for patients and has four main purposes: (i) gathering information on patients' ongoing mental health treatment and consequently provide it to the therapist, (ii) allowing the patient to chat with either the therapist or the *Chat*, whenever the former is not available, (iii) acquiring patient's physiological data via the SDK of the worn wristband, to write these data into the database, and (iv) boosting patients' adherence and motivation to therapy. In fact, in providing these functionalities, the app integrates a

[19] www.next-auth.js.org
[20] www.prisma.io
[21] www.postgresql.org
[22] www.tailwindcss.com
[23] www.tanstack.com
[24] www.github.com/unimib-datAI/micare-app

Token Economy system, addressing the common struggle that characterises traditional therapy methods to maintain consistent patient engagement [47].

Embedded with a user-friendly interface, the *Mobile App* is structured into specific sections:

1. a lifestyle tracking section based on elements of Cognitive Behavioral Therapy (CBT) regarding several topics (*e.g.*, emotions, anxiety, depression, sleep, nutrition, and mood). In other words, this section is dedicated to the patient's diaries;
2. a section reserved for completing digitised psychological tests, *i.e.*, questionnaires;
3. the *Chat*;
4. an informative section for the patient;
5. a calendar section for managing appointments and tasks;
6. a section reserved for avatar customisation.

While the first two account for patient data collection, the last two sections are core to the Token Economy mechanism. The *Mobile App* leverages a gamified approach to transform essential therapeutic tasks, such as medication adherence monitoring, mood tracking, coping mechanism practice, and social interaction exercises, into engaging activities. Completing these tasks makes patients earn reward points, promoting a sense of accomplishment and reinforcing continuous engagement. To further motivate users, the *Mobile App* makes them visualise their progress. Accumulated points translate into a dynamic visual representation, such as a flourishing tree or an evolving design. This visual feedback provides a tangible measure of progress, encouraging users to persist with their treatment plan. Additionally, points can be redeemed to personalise patient's own in-app avatar, adding an element of fun and personalisation to the therapeutic process [48].

Beyond virtual incentives, the *Mobile App* links in-app achievements to tangible rewards, previously agreed upon with the clinician, in the patient's real life. When predefined milestones are reached, therapists can collaborate with the patient's social-support network to provide meaningful rewards, such as rewarding activities, books, or other items aligned with their interests and desires. The integration of real-world reinforcement further incentivises adaptive and desirable behaviors, and strengthens the therapeutic alliance.

The app gathers data from the lifestyle tracking section and the digitised psychological tests (administered by the therapist through the *Dashboard*), which are both completed by the patient via the *Mobile App* itself. These data can be accessed via the *Dashboard* by the assigned therapist and are leveraged by the CDSS. The calendar data are retrieved from the *Dashboard* backend, whereas the **Garmin SDK** are used to get sensor data. All the new data are written into the database.

From a technical perspective, the *Mobile App* employs a technology stack similar to the *Dashboard*. Specifically, it is built with React Native New Architecture[25] and uses the **Expo**[26] framework for simplified development. For styling and component design, **NativeWind**[27] is implemented to manage stylesheets efficiently. Additionally, **TanStack Query** is employed as the tRPC client, facilitating consistent data-fetching operations across the app. **MMKV**[28] is used to store the application local state and settings. As for the *Dashboard*, **Tailwind** is employed for front-end styling.

The *Mobile App* stands out for its marked gamification features, which not only increase patient engagement but also empower them to actively participate in their therapeutic journey. Moreover, by integrating multiple forms of data, such as lifestyle tracking, psychological assessments, and physiological data, it enables the collection of a comprehensive and multimodal data set for supporting both the clinician and the CDSS in making more accurate diagnoses and monitoring conditions over time.

[25]www.reactnative.dev/architecture/landing-page
[26]www.expo.dev
[27]www.nativewind.dev
[28]www.github.com/mrousavy/react-native-mmkv

### 3.3. Chatbot

The ***Chat***[29] (Fig. 4) component of the *MiCare* architecture functions as an AI-driven conversational agent and represents an integral functionality of both the *Mobile App* and *Dashboard*. According to the engaged chatter, it has a double functioning: (i) it delivers accessible, personalised psychological support and information to patients (who interact with it via the *Mobile App*), and (ii) it assists mental health professionals in clinical decision-making via the *Dashboard*, based also on the estimates produced by the CDSS. The *Chat* is developed leveraging SOTA Natural Language Processing (NLP) and ML algorithms able to achieve high accuracy in language comprehension and generation.

Regarding the patients' use of the *Chat*, as primary interaction the *Chat* engages in a conversational assessment to gauge patients' current emotional state, identify potential needs, and address any immediate concerns. This initial exchange helps guide subsequent interactions, adapting messages for a personalised support, based also on the patient profile data including diaries, psychological tests results and real-time physiological data. The *Chat* serves also as a readily available source of information pertaining to various mental health topics, including common emotional disorders, coping strategies, self-help techniques, and relevant support resources. This functionality aims to empower patients with knowledge and facilitate access to strategies to take care of their own mental health, such as promoting emotion regulation, adopting more functional ways of thinking about situations, and planning adaptive behaviours. Additionally, the *Chat* is equipped with skill-based interventions like guided relaxation and mindfulness exercises, and hints towards cognitive reframing which is delivered conversationally. Finally, the *Chat* provides specific answers to inquiries like "What time is my next appointment?" by accessing the calendar API integrated into the *Dashboard* component. Tracking patient interactions, the *Chat* offers tailored feedback, promoting engagement and inviting patients to adhere to their pharmacological medication regimens and complete therapy-related daily tasks. This personalisation ensures that patients receive pertinent, impactful support throughout their interactions.

The *Chat* available on the *Dashboard* is trained to assist clinicians in their daily practice. Specifically, it serves as a conversational agent that can report and signal to the therapist a patient's progress over time, potential areas of concern based on questionnaires answers or physiological parameters considered at risk and, consequently, it can provide timely suggestions to deliver a pertinent and impactful support to the patient. These recommendations are produced based on the analysis powered by the CDSS, as will be explained in more detail in Section 5.

**FastAPI**[30], a web framework that enables API communication, facilitates real-time interactions between users and the chatbot. **LangChain**[31], a powerful AI agent framework, allows the chatbot to integrate structured data from various sources across the *MiCare* platform. The system will use a robust LLM trained in Italian language processing. The considered candidates were **Mistral**[32], LLAMA 2[33], and Falcon[34]. Among these, the Mistral 8X7B model was chosen due to its performance and cost effectiveness, as it is optimally suited for fine-tuning and supports flexible responses to diverse and complex queries, enhancing patient engagement and response variability.

For diagnostic support, the **Phi-3**[35] model, trained on psychological diagnostic manuals such as the DSM-5[49] and the ICD-11[36], provides therapists with reliable and concise diagnostic insights. The model's task-specific nature allows it to achieve high diagnostic accuracy with a compact LLM. The generated insights are also based on the database-stored data, which include the *Mobile App* data, actively inserted by the patient, the *Dashboard* data managed by the clinicians, such as medical records, and the CDSS outputs.

The *Chat* component is designed with careful consideration of ethical implications, ensuring trans-

[29] www.github.com/unimib-datAI/micare-chat
[30] www.fastapi.tiangolo.com
[31] www.langchain.com
[32] www.mistral.ai
[33] www.llama.com/llama2
[34] www.falconllm.tii.ae
[35] www.ollama.com/library/phi3
[36] www.icd.who.int/browse/2024-01/mms/en

parency in its capabilities and limitations. Robust security and privacy measures are implemented to protect patient data and ensure confidentiality in accordance with relevant ethical guidelines and regulations. Clear guidelines are established regarding its role in providing support and information, emphasising that it is not a substitute for professional medical advice or treatment. Mechanisms are implemented to ensure appropriate human oversight and intervention when necessary, particularly in cases of potential risk.

By integrating the *Chat* component, *MiCare* aims to enhance its capabilities in providing comprehensive and accessible mental health support: on the one hand, by delivering patients daily suggestions and timely feedback to their needs, and empowering them to take an active role in managing their mental well-being; on the other one, by supporting clinicians in their daily patients management via data-driven recommendations.

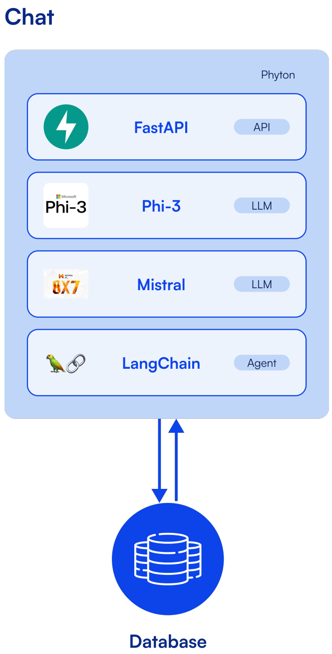


**Figure 4:** Architecture of the *Chat*.

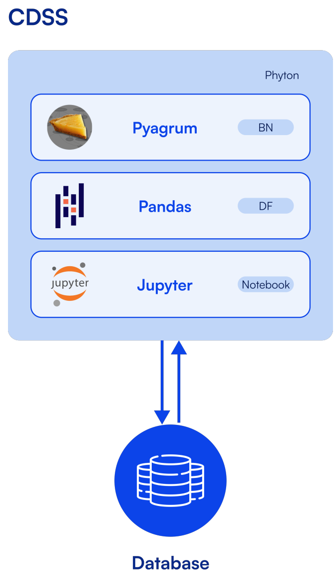


**Figure 5:** Architecture of the *CDSS*.

## 3.4. CDSS

The **CDSS**[37] (Fig. 5) is a BN based predictive model and decision support system developed within the *MiCare* project to assist healthcare professionals in the diagnosis and management of long-term mental health conditions. The use of a BN to develop a prediction model and support decision-making enhances the effectiveness of the work of individual clinicians and teams, providing a benchmark for comparing transparently human autonomous initiatives and conclusions with data-driven insights.

Bayesian Networks (BNs) [50] represent a ML approach eventually capable of determining the probability that, given a set of prognostic factors, a patient is suffering from a particular mental health related issue, or is at risk of developing it or even of exacerbating his current situation. The choice of this ML solution is due to its strength to model complex problems even with strong uncertainty, as well as to its capacity of providing explanation of the evidence, of the model itself, and of reasoning [51]. These elements are essential to guarantee trustworthiness in a delicate context such as the clinical one. Moreover, representing causal or influential relationships between variables in a graphical format, BNs are effective for intuitively interpreting results and combining the numerous and heterogeneous sources of information considered within the *MiCare* ecosystem. In the context of a specific mental

[37] www.github.com/unimib-datAI/micare-cdss

disorders, BNs can integrate factors recognised as risk elements. The selection of relevant variables, aided by expert input, is based on the DSM-5-TR.

The CDSS leverages data stored into the PostgreSQL database and collected through (i) the *Mobile App*, including data from digitalised psychodiagnostic tools and the patient's diaries, (ii) the *Dashboard*, such as medical records and other attachments compiled or uploaded by the mental health professionals, and (iii) wearable devices, after the latter have been processed by the *Signal Processing* component. All these data serve as digital markers of symptoms and can be explicated to the clinician via the *Chat*. They are processed in the **Jupyter** Notebook environment[38] using **Python**[39] programming language, and particularly the following libraries: **pyAgrum**[40] and **Pandas**[41].

Following an extensive validation phase, crucial to test the model's effectiveness, the CDSS eventually provides a new understanding of the psychopathologies and empower mental healthcare professionals to remotely assess patients, focusing on symptoms and patterns with a higher likelihood of remission or appearance. This system is structured, computerised, and fast.

### 3.5. Signal Processing

The ***Signal Processing***[42] (Fig. 6) component takes as input raw PPG and GSR signal data from the wearable devices and outputs features set to be used in the CDSS component. It handles both the signal preprocessing phase and the features extraction, executing them within the **MatLab**[43] environment. Particularly, the **Signal Processing Toolbox**[44] is employed to process the raw data and the cvxEDA [52] function, available at the MathWorks File Exchange repository, is used for the isolation of the GSR phasic and tonic components. Both classical statistical and peak-related features were identified for feature extraction, with the latter being extracted employing custom-built functions.

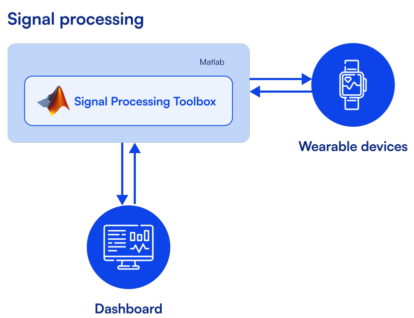


**Figure 6:** Architecture of the *Signal Processing*.

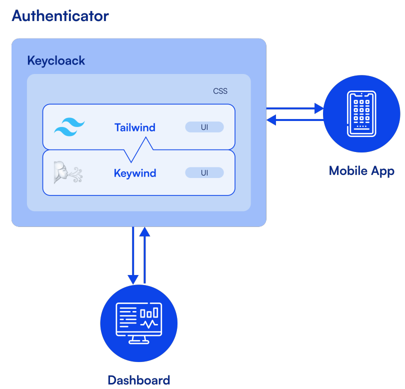


**Figure 7:** Architecture of the *Authenticator*.

### 3.6. Authenticator

The ***Authenticator*** (Fig. 7) component handles authentication and authorisation to access the *Dashboard* and the *Mobile App*. It is managed by the **Keycloak** interface via the OpenID Connect protocol, ensuring secure identity management even in complex contests such as the integration of existing user bases like *Single Sign On* solutions, and synchronising with *Active Directory* or *LDAP* servers. The User Interface (UI) of the login page is styled using a custom theme derived from **Keywind**[45], a theme for

[38] www.jupyter.org
[39] www.python.org
[40] www.pypi.org/project/pyAgrum
[41] www.pandas.pydata.org
[42] www.github.com/unimib-datAI/micare-signal-processing
[43] www.mathworks.com
[44] www.mathworks.com/products/signal.html
[45] www.github.com/lukin/keywind

Keycloak built on **Tailwind** which allows standardising the User Experience (UE) on the login interface, promoting a cohesive UE across both the components. The tRPC APIs interact with this component to assess whether a user has the appropriate permissions to perform actions on specific resources.

## 4. Conclusions

This paper presented *MiCare*, an AI-based technological solution aimed at providing an efficient approach for personalised patient care management, continuous remote monitoring and early identification of abnormalities in the context of mental health disorders. To this purpose, the *MiCare* system encompasses wearable devices, patient records, electronic health records, an AI-powered conversational agent, and a BN-based CDSS, digitalising the entire therapeutic process to bring advantages not only to patients, with young adults being the primary target users, but also to caregivers and mental health professionals. *MiCare* is characterised by an efficient and solid architecture model, which is designed to be constituted by six interconnected components whose functionalities were extensively described in Section 3.

Research into the SOTA of CDSS for mental health and of the integration of wearable sensor data in clinical applications underscored the need for a platform that bridges these technologies within the psychological field. *MiCare* addresses this need by integrating wearable sensor data into a CDSS, empowering therapists to manage patients remotely and via passively and continuously collected physiological data. The strengths advanced by *MiCare* as a system for remote mental health monitoring and early disorder detection can be summarised in the following:

- the broader coverage of mental health disorders, compared to other SOTA CDSS and developed mental health support platforms, guaranteeing a broader usability for therapists and an ampler coverage for patients, especially considering the comorbidity of some mental issues which cannot always be limited to a single disorder;
- the multichannel feature of the system, as it can be experienced through the *Dashboard* by the therapists, and via the *Mobile App* by patients. The *Mobile App* represents an attractive alternative in terms of cost-effectiveness as it removes the necessity of visiting the institution in person and it allows to easily perform tests and collect and analyse data, towards a remote and preventive mental health management approach;
- the use of AI for predictive analytics and natural language generation in the chatbot component, and in decision support with the CDSS component;
- the acquisition of physiological signals as a passive and remotely collected data source that, in conjunction with traditional psychological measures, such as psychological assessment results and behavioural tracking, allow to gather a data-driven, quantitative evidence supporting diagnosis, monitoring, and clinical decision-making also in the context of mental health disorders. This extends the SOTA domain of application of physiological data within the field of medicine;
- the advantage it brings at a double level to both the therapist, who can efficiently manage the patients' needs also in a remote modality and based on the insights furnished by the CDSS, and the patient, with an active and positive engagement in the therapeutic process, via a gamification approach, but requiring. Moreover, it is planned to pave the way for contributing to research at national level as well as the future plan of data integration for research purposes.

While *MiCare* holds promise, it is crucial to acknowledge the inherent challenges of implementing novel technologies within the sensitive mental health landscape. Data privacy and security demand constant vigilance, necessitating robust safeguards and adherence to evolving regulations like GDPR and the AI Act. *MiCare* offers monitoring and support tools while ensuring the availability of human intervention when necessary. Clinicians' comprehensive training is essential for the platform's effective utilisation, emphasising its role as a complement to human interaction, not a replacement.

The use of real-time and noninvasive sensors embedded into wearable devices, in combination with patients' self-reported data, all of which can be collected remotely, and medical records, allows for a continuous monitoring of patients, providing sufficient information for determining health status, preliminary medical diagnosis and a patient-centred personalised medicine for a variety of mental health issues. The integration of physiological data with traditional assessment tools promises to bridge the gap between subjective experience and measurable biomarkers, fostering a more comprehensive understanding of mental health dynamics. Finally, the remote monitoring modality provided by *MiCare* favours equitable access to patients, avoiding exacerbating existing disparities in care.

## Declaration on Generative AI

The authors have not employed any Generative AI tools.

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