# Complexity index from a personalized wearable monitoring system for assessing remission in mental health

# Complexity Index From a Personalized Wearable Monitoring System for Assessing Remission in Mental Health

Antonio Lanata, *Member, IEEE*, Gaetano Valenza, *Member, IEEE*, Mimma Nardelli, Claudio Gentili, and Enzo Pasquale Scilingo, *Member, IEEE*

***Abstract*—This study discusses a personalized wearable monitoring system, which provides information and communication technologies to patients with mental disorders and physicians managing such diseases. The system, hereinafter called the PSYCHE system, is mainly comprised of a comfortable t-shirt with embedded sensors, such as textile electrodes, to monitor electrocardiogram-heart rate variability (HRV) series, piezoresistive sensors for respiration activity, and triaxial accelerometers for activity recognition. Moreover, on the patient-side, the PSYCHE system uses a smartphone-based interactive platform for electronic mood agenda and clinical scale administration, whereas on the physician-side provides data visualization and support to clinical decision. The smartphone collects the physiological and behavioral data and sends the information out to a centralized server for further processing. In this study, we present experimental results gathered from ten bipolar patients, wearing the PSYCHE system, with severe symptoms who exhibited mood states among depression (DP), hypomania(HM), mixed state (MX), and euthymia (EU), i.e., the good affective balance. In analyzing more than 400 h of cardiovascular dynamics, we found that patients experiencing mood transitions from a pathological mood state (HM, DP, or MX—where depressive and hypomanic symptoms are simultaneously present) to EU can be characterized through a commonly used measure of entropy. In particular, the SampEn estimated on long-term HRV series increases according to the patients' clinical improvement. These results are in agreement with the current literature reporting on the complexity dynamics of physiological systems and provides a promising and viable support to clinical decision in order to improve the diagnosis and management of psychiatric disorders.**

***Index Terms*—Bipolar patients, complexity, heart rate variability (HRV), mental disorders, nonlinear analysis, sample entropy (SampEn), wearable monitoring system.**

## I. Introduction

BIPOLAR disorder (BD) is a chronic psychiatric condition [1] recognized to be one of the most common and dangerous disorders of affectivity (diagnostic and statistical manual of mental disorders (DSM-IV-TR) [2]).

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People affected by BD manifest drastically altered mood regulation, experiencing unbalanced mood shifts among depression, mania or hypomania, and mixed states (where both symptoms of depression and hypomania are present at the same time), thus having a significant impact on the patients' social, occupational, and general functioning and wellbeing. As stated peviously, BD strongly affects the patients' quality of life (QoL), even during time periods free of clinical relevant symptomatology [3], [4]. Such a reduced QoL can also be related to a significant loss of cognitive performance [5]. In addition, BD patients often experience anxiety, which is associated with suicide attempts, lifetime alcohol abuse, and psychosis [6].

Depression is characterized by sadness and hopelessness (including suicidal ideation), whereas mania leads to euphoria or irritability, excessive energy, hyperactivity, hypertrophic self-esteem, and a reduction of the need of sleep. The moderate form of mania is called hypomania. Periods in which patients do not show enough pathological signs to be considered in one of the aforementioned clinical states are called euthymic states. Despite the high managing costs and severity of the disease [7]–[10], in current clinical practice, BD diagnosis relies only on interviews and scores from psychological questionnaires, the physician's own expertise, as well as, the patient's subjective description of the symptoms. Moreover, BD is always characterized by comorbidity, i.e., the simultaneous presence of symptoms, which are shared with other psychiatric disorders. All the mentioned issues associated to BD can likely lead to subjective interpretations, inconsistencies, and misdiagnoses [11].

Disease management and treatment are often associated with pharmaceutical and psychosocial interventions. In many cases, hospitalization is also required in the presence of severe manic or depressive episodes. Nevertheless, in current clinical practice, neither biological/physiological nor other objective markers are used to support such a diagnosis and treatment. Of note, the treatment response is still one of the major problems in psychiatric management, especially in psychopharmacological interventions. Clinicians, in fact, are often obliged to a "trial and error" approach, which consists of the prescription of a treatment without being sure of its effectiveness [12].

To overcome these limitations, in this study, we propose a novel personalized system comprised of a wearable monitoring system with embedded sensors and a smartphone to better manage patients affected by mental disorders such as BD: The PSYCHE system. It is based on the novel paradigm related to the possibility of recognizing mood states through information gathered from the autonomic nervous system (ANS) [13]–[17]. The ANS dynamics, in fact, has been already proven to play a crucial role in discerning pathological mental states associated to BD [18].

Previous studies on sleep [19], circadian heart rate rhythms [20], and the hormonal system [21] emphasized that there may exist physiological changes that are in agreement with the clinical status and may be considered predictors of clinical changes [22]–[23]. However, none of the previous studies have led to the development of an effective system to be introduced into the current clinical practice. This could be due to the heterogeneity of the mood disorders in terms of psychophysiological, neuroendocrine, and neurobiological correlates with respect to the simple clinical phenotypes adopted for clinical purposes [19], [20], [25], [26]. Of note, many efforts have been made to investigate biomarkers of BD regardless of setting up pervasive, comfortable, and wearable assisting living systems for the BD management. In previous studies [15]–[17], [27], we provided a preliminary description of the PSYCHE system showing how a multiparametric data-mining approach can be usefully employed to discriminate different pathological mood states associated to BD. In these previous studies, we validated the PSYCHE concept performing both feasibility studies and preliminary experimental acquisitions of mild bipolar manifestations. In this study, we applied the PSYCHE system to severe BD manifestations showing that long-term acquisitions along with high-level signal analysis can provide robust results in terms of treatment response, revealing when the clinical follow up is going into remission. Here, after going into detail about the system and showing how a patient–physician closed loop is implemented by means of user and professional interfaces, we will show how the PSYCHE system can be used on hospitalized patients in order to investigate the response to treatment on BD patients with severe symptoms. Although patients are in clinical settings, they are asked to wear the PSYCHE system for monitoring over long period of time. We propose a simplified approach focusing on only a complexity measure, i.e., sample entropy, estimated on long-term HRV series. More specifically in this study, we aim at verifying the hypothesis that a synthetic and personalized physiological parameter able to characterize the course of the pathological mental state evolution toward EU may exist. This challenging goal is achieved by exploiting the PSYCHE platform, which enables for long-term monitoring of bipolar patients.

Currently, several sensor-based wearable systems for health monitoring used for research scope exist [28]–[32] but, at present, the PSYCHE platform is the only one applied to patients affected by severe manifestations of BD. It is worthwhile noting that BD requires lifelong management, and individuals have to remain constantly vigilant for warning signs that might indicate a relapse. In the standard practice, this latter aspect is performed by self-tracking, which is difficult to maintain over an extended period. Even though an increasing number of studies demonstrated the ability of a wearable system to assist in the self-tracking, this cutting-edge technology is absent from the mental health treatment [33]. In addition, it is vital that patients as well as clinicians accept technological supports.

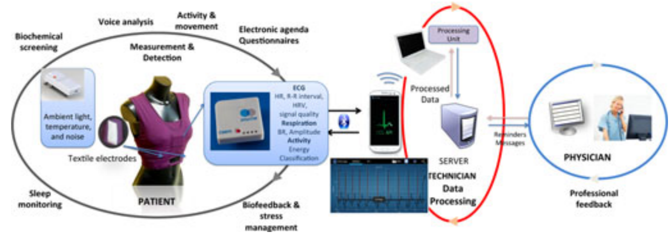


Fig. 1. Overview of the PSYCHE architecture involving wearable monitoring system, mobile application, and feed-back to patient and clinician.

Patient acceptance is paramount because low acceptance can lead to reduced adherence or nonuse. Acceptance is, therefore, a critical factor to consider when introducing sensing in the management of mental illnesses, which can carry significant stigma. Therefore, the textile-integrated platform together with the smartphone framework offered by the PSYCHE system led to a higher level of acceptance with respect to all of the systems that are comprised of many off-the-shelf sensors [34].

This paper is organized as follows: Section II describes the technological details of the PSYCHE system, particularly emphasizing the patients' benefits from this assisted living system. Section III reports the signal processing techniques implemented in the embedded electronics of the wearable monitoring systems as well as in the remote central server, showing how data are processed for clinical state identification. In Section IV, an evaluation study performed on a group of ten BD patients, along with the experimental protocol and the achieved results, is described. Finally, Section V reports on the conclusion and discussion of the obtained results.

## II. PSYCHE System

The main idea behind the PSYCHE system is grounded on a novel naturalistic approach of BD patient monitoring, aiming at providing parameters, indices and trends in order to better assess pathological mood states [14], [15], [17], [33]. The system provides a continuous communication and feedback to the patient and physician through a closed loop in order to facilitate disease management by fostering an innovative way to collaborate. Indeed, constant monitoring and feedback (to both patients and physicians) constitute the new key to manage the illness, to help patients, to facilitate interaction between patient and physician, as well as to alert professionals in case of relapse and depressive or manic episodes. The closed-loop system, shown in Fig. 1, is implemented on the patient side through a noninvasive wearable platform to acquire physiological signals from the patient as well as from a mobile platform (i.e., a smartphone) for multiple uses. It records the physiological signals, acquires speech during a dedicated task, allows patients to fill out a mood agenda and daily self-administered questionnaires, and finally, sends data to a remote server wherein the processing block is located. On the professional side, a central remote server is dedicated to analyze the data acquired from the patients and to provide results to clinicians for future evaluations. The proposed architecture was developed in the frame of the European project PSYCHE


Fig. 2. Prototype of the PSYCHE wearable monitoring system showing a t-shirt with embedded textile sensors. From [17].

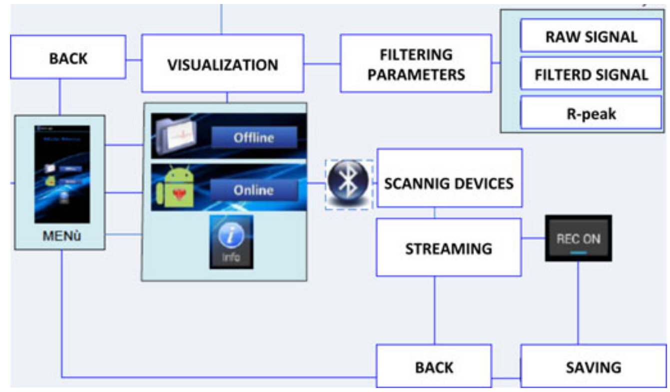


Fig. 3. Mobile platform digram for physiological signal acquisition from the wearable platform.

(FP7/ICT, Grant 247777), whose aim were to develop a pervasive and personalized monitoring system for care assessment in mental health [15]–[17], [27].

Concerning the physiological measures, the PSYCHE system is able to perform long-term ANS monitoring through a comfortable textile-based platform, produced by Smartex srl (Prato, Italy). It is comprised of a sensorized t-shirt able to acquire ECG, heart rate variability (HRV), and respiration activity [34], along with an embedded electronics able to acquire, preprocess, store, and send the acquired data. In addition, an internal triaxial accelerometer is able to monitor movement activity including its classification (i.e., supine, sitting, sleep posture, etc.), see Fig. 2. It is worthwhile noting that the wearable system makes use of dry textile-based electrodes. These electrodes have a special multilayer structure that increases the amount of sweat and reduces the rate of evaporation reaching electrochemical equilibrium between skin and electrode after 10 s, thus showing a good signal quality [37]–[39]. As a matter of fact, the signal quality is prevalently given by stable electrode– skin interface impedance, which is mainly governed by the air gap between the interfaces. For this reason, the presence of a soft layer in this multilayer electrode provides a skin adaptive electrode soft enough to adapt to the geometry of the biological site, and thereby, significantly reduce the air gap between skin and electrode. Moreover, a soft electrode maintains contact even during motion, rubbing, and sliding of the electrode over the skin that is one of the major sources of the motion artifact [40].

Two different shirt typologies for women and men were designed as well as a specific sensorized bra for women. A wide range of sizes were available. In particular, the garments were made of elastic fibers allowing for tight adhesion to the user's body, piezoresistive fibers to monitor fabric stretching (and consequently, respiration activity), and metallic fibers knitted to create fabric electrodes to monitor the ECG. These materials are knitted together and are fully integrated in the garment without any mechanical and physical discontinuity, creating areas with different functionalities.

The shirt was designed taking into account the thermal comfort, both in the selection of the yarns and in the stitch structure, several zones with an open net were inserted, and a polyamide yarn with antibacterial properties and a natural feeling was used as a basic component. As a matter of fact, garments were made of commercial yarns, already tested (and certified) for contact with human skin, and can be easily washed, and in need, disinfected.

The electronic device of the wearable platform sends the collected physiological data to a mobile device (i.e., a smartphone) through a bluetooth communication channel. The mobile application, which is based on an object-oriented java programming for the Android 4.01 operating system, stores physiological data on a 128 GByte Secure Digital (SD) card, and during the inactive period of the PSYCHE system forwards them to the central server by means of a wi-fi internet TCP/IP protocol. Fig. 3 shows the block diagram of the app acquisition stage. The developed app can be used in two modalities , i.e., “Online” and “Offline.” First of all, the application foresees a bluetooth scanning port for detecting the wearable device; once the device is detected, the physiological data streaming starts. The “Offline” mode is designed for setting up system configuration and checks the quality of the physiological signs when the system is given to the patient first. Fig. 3 shows the block diagram of the acquisition, filtering, and visualization of signals. In this modality, signals can be visualized in real time (see Fig. 4). After that, the app is ready to be used in ”Online” mode, in which the systems is automatically managed and the app runs as a background service during this modality the data are stored in the SD card (see the down side of the Fig. 3). In the centralized server, the patients' physiological and behavior data are processed using a personalized model in order to properly correlate the obtained parameters with the mental status of the patient. The general model that is adaptable to each patient is based on a data-mining concept. It includes several algorithms used for identifying the mood clinical state, including data reduction and automatic classification of the extracted features. Hereinafter, it will be identified as the interpretation unit (IU). A simplified scheme of the IU concept is shown in Fig. 5. Once the features are extracted, a dimension reduction is performed by means of both feature reduction (e.g., principal component analysis) and selection (e.g., statistical significance). Data gathered from patients during the acquisition phase are stored in a database

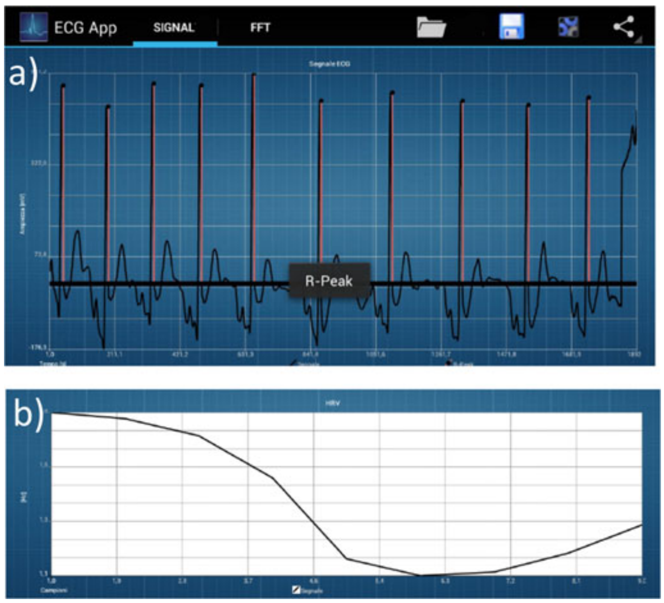


Fig. 4. Example of signals acquired from the wearable system: a) ECG; b) obtained HRV;.

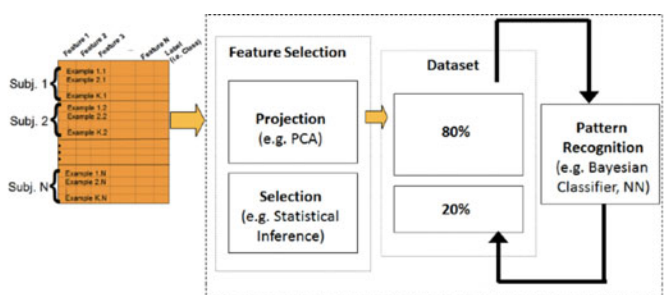


Fig. 5. Data-mining concept implemented in the PSYCHE system: after the feature selection procedure, statistics and pattern recognition algorithms are applied, running into the centralized server.

called management platform (MP). For each new acquisition, the IU provides the predicted status as the output of the trained classifiers [41]. The patient–physician closed-loop system is comprised of two logical blocks: the *Storage Area* where raw signals and other patient's information are stored, and the *Data-Mining Area* that produces predictive results on the patient's state based on the analysis of the uploaded data. Patients at home are connected to the system, which automatically uploads data. These data are used, together with other data of the same patient already present in the MP to extract data-mining results that will be shown to the attending physician, who will use them to optimize patient's therapy, thus *closing the loop* (e.g., sending a text message "see you tomorrow for a new visit" or whatever personalized message).

In addition, other signals such as biochemical data obtained through portable device (e.g., saliva-based lithium detection as well as stress-related hormones, etc.), voice and electrodermal response have also been included into the monitoring platform, along with behavioral data such as sleep quality, physical activity, questionnaires, mood agenda, sleep agenda, medication intake, and diary [15]–[18], [27].

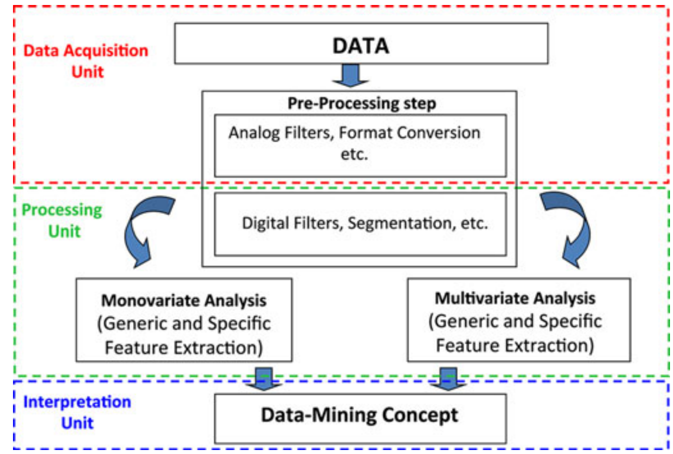


Fig. 6. Block diagram of the PSYCHE processing platform, whose details are reported in [15].

## III. Methodology of Biomedical Signal Processing

Signal processing and data-mining techniques are implemented in the embedded electronics of the wearable monitoring systems as well as in the remote central server, and aim at analyzing the acquired data in order to maximize the information for the definition of the patient's clinical state. Of note, only part of the preprocessing procedures is implemented in the embodied electronic device, while the remaining part is transmitted to a smartphone, and then, to a central database for further analysis. The current state-of-the-art of biomedical signal processing as well as multifunctional and multiparametric analysis are applied to all of the acquired physiological data, including results also from questionnaires, clinical and medical information, and patient characteristics (age, gender, etc.). A processing unit was developed following the schema reported in Fig. 6.

Although the PSYCHE system was based on a multiparametric approach, processing the features from HRV, respiration signal, activity, voice, and questionnaires all together, using both linear and nonlinear methodologies [42], this study is focused only on the elaboration of a single signal, i.e., sample entropy (SampEn), which is estimated on long-term HRV series. SampEn is a measure of complexity of the HRV, and it is defined as the negative natural logarithm of the conditional probability that two sequences similar for $m$ points remain similar at the next point [43]. In the literature, it has been already showed the relationship between complexity measure of the HRV and the mental health status [44]. In the next section, the mathematical derivation of such an entropy measure is described in detail.

### A. SampEn

In order to perform the SampEn calculation, the phase space of the HRV series must be estimated. This task can be performed using Taken's theorem through two parameters: $m$ the embedding dimension, and $r$, the margin of tolerance. The Entropy calculation of short and noisy time-series data was first studied by Pincus [45] by defining the Approximate Entropy, which has subsequently been followed by the SampEn [43], [46]–[48].

Specifically, starting from the vectors $X_1, X_2, ..., X_{N-m+1}$ in $\mathbb{R}^m$ defined by $X_i = [u(i), u(i+1), ..., u(i+m-1)]$, the distance between two vectors $X_i$ and $X_j$ is defined according to the Taken's formulation in his studies on the high-dimensional deterministic system [49], [50]:

$$d[X_i, X_j] = \max_{k=1,2,...,m} |u(i+k-1) - u(j+k-1)|. \quad (1)$$

For each $i$, with $1 \le i \le N-m+1$, the variable $C_i^m(r)$ is defined as

$$C_i^m(r) = \frac{\text{Number of j such that } (d[X_i, X_j] \le r)}{N-m+1}. \quad (2)$$

Starting from the following definition

$$C^m(r) = \frac{\sum_{i=1}^{N-m+1} \log C_i^m(r)}{N-m+1} \quad (3)$$

the SampEn is computed through the expression[41]

$$\text{SampEn}\,(m,r,N) = -\ln \frac{C^{m+1}}{C^m}. \quad (4)$$

In this study, we used standard values for $r$ and $m$ parameters, which have been suggested in previous studies dealing with RR interval series [43]: $m = 2$ and $r = 0.20 * \text{std}$ (std = standard deviation of time series).

## IV. Case Study: PSYCHE System for Patients with Severe Bipolar Disorder

This study aims at validating the PSYCHE system in terms of supporting the diagnosis and helping in the prognosis of patients affected by severe bipolar disorders. Specifically, this study investigates the PSYCHE system ability to detect early the response to treatment in bipolar patients who also underwent electroconvulsive therapy.

### A. Patient Recruitment and Experimental Protocol

Ten patients were recruited and monitored during an acute episode and followed until clinical remission.

Patients were recruited at the Pisa University Hospital within the Second Chair of Psychiatry and the chair of Clinical Psychology. Patients had to express their written informed consent to participate in the study and fulfill the following inclusion criteria:

1) age between 18–65 years;
2) clinical diagnosis of bipolar disorder and the presence of a mood episode;
3) the absence of high risk suicidal behaviors;
4) occurrence of at least a change of treatment (dosage and/or drugs) within the two weeks earlier than the recruitment time.

The experimental protocol for the PSYCHE project was approved by the ethical committee of the University of Pisa, study 3148, 010-PSYCHE-001. In this study, we recruited acutely depressed and depressed/hypomanic, hospitalized patients. This choice was motivated by the following reasons.

1) Hospitalized patients have, in general, full-bloomed pathological states. Thus, the changes in clinical states would have been more marked as, presumably, the effect of these changes on psychophysiological parameters.
2) The PSYCHE system is in itself a naturalistic study that does not imply the control for medication intake. On the other hand, hospitalized patients can undergo a change in medication prescription, and therefore, that can be followed in terms of clinical and psycho-physiological changes due to response to treatment.
3) The goal of this study was to assess if there are psychophysiological changes that might predict remission. For this reason, hospitalized patients are an ideal candidate to this end. Given the fact that they were under constant supervision by health care professionals, they could be evaluated during remission.

The clinical history of the enrolled ten patients during this study is detailed in Table I.

TABLE I
Clinical Mood States of the Patients Under Study

| Patient | Acq.1 | Acq.2 | Acq.3 | Acq.4 | Acq.5 |
|---|---|---|---|---|---|
| Pz01 | DP | EU | | | |
| Pz02 | MX | MX | DP | DP | EU |
| Pz03 | MX | EU | | | |
| Pz04 | DP | EU | | | |
| Pz05 | DP | DP | EU | | |
| Pz06 | DP | DP | DP | EU | |
| Pz07 | MX | MX | DP | EU | |
| Pz08 | MX | MX | EU | | |
| Pz09 | DP | EU | | | |
| Pz10 | DP | EU | | | |

EU stands for euthymia state; DP stands for depression state; MX stands for mixed state; Pz stands for patient; Acq stands for acquisition.

### B. Experimental Results

In this study, HRV was acquired and processed during normal activity in the clinical settings. In a previous study [51], it has been shown that linear-derived parameters are inadequate to discern healthy subjects and patients with major depressive disorders as they have a variance as high as to not be able to infer an appreciable difference between the two groups. On the contrary, nonlinear measures such as the entropy-based ones allowed for discriminating of depressive patients from healthy subjects, always showing a significant decrease of the complexity in the pathological group [52]. Results from the current study show that the SampEn, evaluated on data coming from the PSYCHE platform, can be considered as a viable and simple biomarker of response to treatment in severe bipolar patients.

Figs. 7–11 and Table II show the SampEn trend for each of the considered BD. It is straightforward to notice that the SampEn values increase as the mood state goes from mixed state (the most severe pathological mental status) to euthymic state

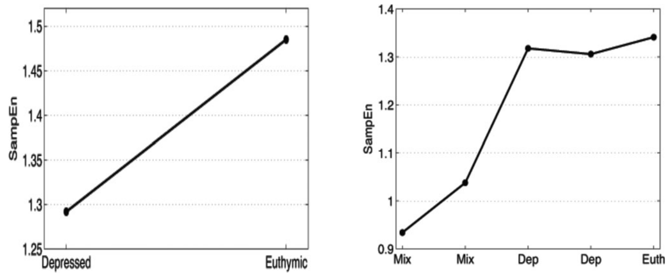


Fig. 7. SampEn values computed on HRV series for patients Pz01 and Pz02.

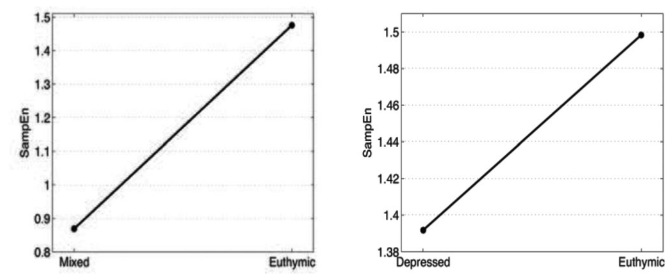


Fig. 8. SampEn values computed on HRV series for patients Pz03 and Pz04.

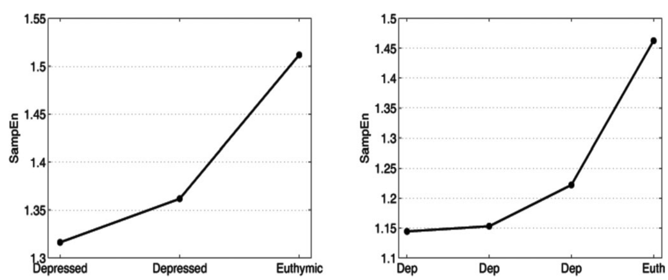


Fig. 9. SampEn values computed on HRV series for patients Pz05 and Pz06.

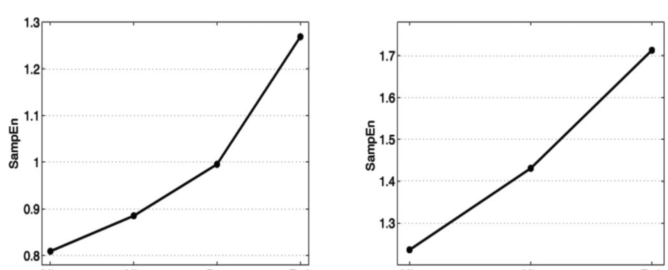


Fig. 10. SampEn values computed on HRV series for patients Pz07 and Pz08.

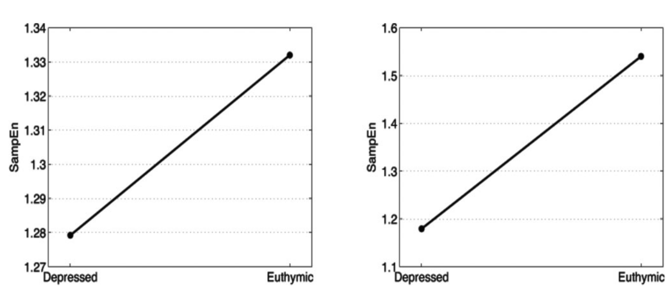


Fig. 11. SampEn values computed on HRV series for patients Pz09 and Pz10.

TABLE II
SampEn Values Associated to BP Patients Under Study

| Patient | Acq.1 | Acq.2 | Acq.3 | Acq.4 | Acq.5 |
|---|---|---|---|---|---|
| Pz01 | 1.29 | 1.49 | | | |
| Pz02 | 0.93 | 1.04 | 1.32 | 1.31 | 1.34 |
| Pz03 | 0.87 | 1.48 | | | |
| Pz04 | 1.39 | 1.50 | | | |
| Pz05 | 1.30 | 1.36 | 1.51 | | |
| Pz06 | 1.14 | 1.15 | 1.22 | 1.46 | |
| Pz07 | 0.81 | 0.88 | 0.99 | 1.27 | |
| Pz08 | 1.34 | 1.43 | 1.71 | | |
| Pz09 | 1.28 | 1.33 | | | |
| Pz10 | 1.18 | 1.54 | | | |

TABLE III
Experimental Results on the Intersubject Analysis Among Different Mood States

| | Mixed-State | Depression | Euthymia |
|---|---|---|---|
| 95% Confidence interval (*t*-Student) | [0.8663, 1.1911] | [1.1890, 1.3045] | [1.3930, 1.5333] |

(the good affective balance) through depression. According to these considerations, the coherent trends highlighted using the intrasubject analysis are informative results.

In order to generalize the results, Table III shows a 95% confidence interval (CI) for each of the considered mood states.

The CI was calculated according to the following formula:

$$\text{C.I.} = \overline{x} \pm t_{0.05,\ni}\sigma/\sqrt{n} \quad (5)$$

where $\overline{x}$ and $\sigma$ are the mean value and standard deviation of $x$, respectively, and $n$ is the number of samples of the vector $x$. The variable $t_{0.05,\ni}$ stands for the $t$ -Student variable with statistical significance $0.05$ and $\ni = n - 1$ degrees of freedom.

Of note, the CI among the pathological mental states are not overlapped, suggesting the promising role of the PSYCHE system as a decision support system for BD patients having severe symptoms.

## V. Conclusion and Discussion

We presented a clinical application of the PSYCHE platform, that is a personalized wearable monitoring system for care in mental health. The wearable platform was tested during the course of the PSYCHE project to be able to comfortably acquire physiological signals from severe BD patients during long-term acquisitions. Moreover, embedded mobile device was proven to be a suitable platform to collect and transmit data to the server for further processing stages. The PSYCHE architecture has been designed and developed with the aim of collecting a large amount of data and implementing a data-mining strategy to identify the current clinical status as well as predict early the next mood state transition. In this study, we processed only a single signal acquired with the platform in order to investigate the response to treatment. As a matter of fact, we demonstrated that the PSYCHE system can be usefully employed in assessing the response to treatment in BD patients with severe symptoms.

The uncertain positive effect of pharmacological treatments, in fact, is widely accepted to be one of the major clinical problems, even if appropriate drugs are administered. Clinicians often need to try and adjust their treatments if they realize that the expected clinical response is not coming. Through the PSYCHE system and the related long-term recording of ANS signals, it was possible to extract and analyze simple but effective complex measures such as the SampEn, which have been demonstrated to play an important role in several psychiatric as well as cardiovascular disorders [52], [53]. SampEn and other complexity measurements have been demonstrated to be reduced in cardiovascular disorders as well as in depression and insomnia [52], [54], [55]. Complexity measurements were also shown to decrease when healthy individuals were subjected to an acute stress [54]. As it was expected, also in our sample we found that SampEn varies almost linearly when pathological states go toward euthymia including a clear distinction between psychopathological states with different levels of severity and with different clinical characteristics (like mixed state and purely depressive states). Moreover, following the trend of these parameters we were retrospectively able to state that the patients were going to remit. Therefore, as compared to the available literature, we are able to extend the relationship between complexity reduction and pathological state, already verified in major depression, to bipolar disorders. We also show a trend that seems to link the presence of (hypo)maniac states (in mixed states) to a even bigger loss of complexity as compared to depressive states. These findings might suggest that SampEn can be considered a marker of clinical severity in bipolar disorders. Indeed other studies have shown, at a group level, differences between patients and controls both in acute depressive states or in remitted euthymic states [57]. However, no study was able to assess this difference in SampEn at a single subject level, and longitudinally, in the same patient through different pathological mood states. Finally, we were able to find a similar pattern of SampEn changes at a single subject level: the achieved results show coherent behavior of the SampEn in all of the patients. Although these results are very preliminary since obtained on a reduced, although consistent, population, they encourage us to hypothesize that this complexity measure can be used as an early and valid indicator of the treatment response of each patient toward remission. A change in SampEn measurements might be a preclinical marker of the treatment response. From a clinical perspective, such early indications would greatly help to improve the treatment and care, allowing for more rapid changes in ineffective treatments and faster optimization of effective treatments. This would have a possible relevant relapse on psychiatric clinical practice since the uncertain outcome of pharmacological treatments is widely accepted as one of the major clinical problems, even if appropriate drugs are administered.

Increasing the number of acquisitions from each patient in a larger group of patients may also allow for simple prediction approaches based on linear or nonlinear combinations of values of previous acquisitions. This approach would allow the determination of mood outcome not only retrospectively, as in this paper, but also as a real forecast having tremendous impact on clinical course and quality of life of the patients.

To conclude, we showed how the platform was used as viable support to clinical decision. The closed-loop system implemented in the architecture of the PSYCHE system, where a continuous biofeedback to physicians and patients is carried out, resulted to be a novel approach in the psychiatric disorder management. Moreover, the continuous interaction between clinicians and patients improves the quality of life of patients helping the clinicians in the diagnosis and preventing relapses. In addition, the proposed system is to be intended as a personalized system, which can be tailored to a single patient's needs.

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