Combining continuous smartphone native sensors data capture and unsupervised data mining techniques for behavioral changes detection: A case series of the Evidence Based Behavior (eB2) study.

Sofian Berrouiguet*,1,2,3 MD, David Ramírez4,5 PhD, María Luisa Barrigón6,7 MD PhD, Pablo Moreno-Muñoz4,5, Rodrigo Carmona6 MD, Enrique Baca-García6,7,8 MD PhD, Antonio Artés-Rodríguez4,5,8 PhD

1. Department of Psychiatry and Emergency, Brest Medical University Hospital, Brest, France.
2. Logics in Uses, Social Science and Information Science department, Telecom Bretagne, Plouzané, France.
3. SPURBO EA 7479, UBO.
4. Universidad Carlos III de Madrid, Leganés 28911, Spain
5. Gregorio Marañón Health Research Institute, Madrid 28007, Spain
6. Department of Psychiatry, Fundación Jiménez Díaz Hospital, Madrid 28040, Spain
7. Department of Psychiatry, Autónoma University, Madrid 28040, Spain
8. CIBERSAM (Centro de Investigación en Salud Mental), Carlos III Institute of Health, Madrid, Spain.

* Corresponding author: CHRU Cavale Blanche University Hospital of Brest Boulevard Tanguy Prigent 29609 Brest Cedex (France), sofian.berrouiguet@chu-brest.fr.

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Abstract

Background:
The emergence of smartphones, wearable sensor technologies, and smart homes allows the non-intrusive collection of activity data. Thus, health-related events such as Activities of Daily Living (ADLs, e.g., mobility patterns, feeding, sleeping, ...) can be captured without the patient’s active participation. We designed a system able to detect changes in the mobility patterns based on the smartphone’s native sensors and advanced machine learning and signal processing techniques.

Objective:
The principal objective of this work was to assess the feasibility of detecting mobility patterns changes in a sample of outpatients suffering from depression using the smartphone’s sensors. The proposed method processed the data acquired by the smartphone using an unsupervised detection technique.

Method:
Thirty-eight outpatients from the Hospital Fundación Jiménez Díaz Psychiatry Department (Madrid, Spain) participated in the study. The eB2 app was downloaded by patients on the day of recruitment and configured with the assistance of the physician. The app captured the following data: inertial sensors, physical activity, phone calls and message logs, app usage, nearby Bluetooth and Wi-Fi connections, and location. We applied a change-point detection technique to location data on a sample of 9 outpatients recruited between April 6th, 2017 and December 14th, 2017. The change-point detection was based only on location information, but the eB2 platform allowed for an easy integration of additional data. The app remained running in the background on the patient’s smartphone during the study participation.

Results:
The principal outcome measure was the identification of mobility pattern changes based on an unsupervised detection technique applied to the smartphone’s native sensors data. Results from five patients’ records are presented as a case series. The eB2 system detected specific mobility pattern changes according to the patient’s activity, which may be used as indicators of behavioral and clinical state changes.

Discussion:
The proposed technique was able to automatically detect changes in the mobility patterns of the outpatients that took part in this study. Assuming these mobility pattern changes correlated with behavioral changes, we have developed a technique that may identify possible relapses or clinical changes. Nevertheless, it is important to point out that the detected changes are not always related to relapses and that some clinical changes cannot be detected by the proposed method.
Introduction

Data capture in patient environment
Web-based and smartphone applications offer new opportunities for patient monitoring. The integration of these tools into medical practice has heralded the electronic-health (e-health) era. E-health involves the integration of new technologies into routine clinical practice by increasing networking possibilities between patients and clinicians. Recent trials using mobile electronic devices have proven successful in real-world and real-time monitoring and have improved the assessment possibilities in a large panel of clinical settings [1]. The assessment of the patient's dynamic relationships between events and disease course is enhanced by the development of momentary data collection strategies, such as experience sampling methods (ESM) and ecological momentary assessment (EMA). These approaches, which rely on delivering informative contents and self-administered questionnaires, reduce the recall bias as they are done in quasi-real time, but they face many limitations, including poor reliability of the data, the burden and intrusiveness for the patient, and data security issues [2].

Electronic devices are also able to perform passive (or autonomous) data gathering, i.e., to extract information about the users without any effort on their part. Actigraphy, geolocation, and communication activity are usual features of current smartphones and may be indicators of the patient's behavior if they are properly processed. Advances in sensors technology, and novel textile-electronic integration techniques also draw new perspectives for behavior ecological assessment (BEA). Moreover, it is currently possible to find commercially available wearable sensing technologies for several wellness and clinical purposes: simple heart rate monitors (HR) [3], rehabilitation after surgical intervention [4], monitors of physical activity or sleep quality assessment [5]. Overall, an extensive panel of physical and mental conditions (e.g., insomnia, diabetes, problems associated with older age, cardiac problems, or respiratory problems) can be remotely monitored by the appropriate health care professional: physicians, doctors, or nurses. These devices are often connected to a smartphone, which increases the networking capabilities and the user experience. The collected data can be processed and transferred over the Internet to a remote clinical back-end server for further analysis, assessment, and decision making and intervention if need be.

The monitoring of activity of daily living and episodic episodes
The emergence of smart homes and wearable sensor technologies allows non-intrusive collection of activity data [6]. Thus, health-related events such as Activities of Daily Living (ADLs, e.g., feeding, sleeping) and the patient's mobility patterns can be captured without their active participation [7]. Monitoring behavioral changes of psychiatric patients and their ability to carry out their ADLs will likely improve the knowledge about the disease course. For example, the detection of changes in behavioral patterns may help to detect emerging disorders [8]. Additionally, smart home and ambient assisted living (SHAAL) systems use sensors and other devices that are either wearable or integrated in the patient's home and have been used to assess the effect of undesirable symptoms and cognitive impairment on ADL functions [9] or to detect emerging disorders based on changes in the patient's behavior [10]. The ease of access to smartphone technology for the general population and recent technological advances in smartphone integrated sensors are paving the way for behavioral changes detection, based only on activity assessment. Physical activity assessment is usually based on
findings from brief, regularly scheduled in-person appointments or self-questionnaires [11]. Although widely used, this approach reduces assessment to cross-sectional observations that miss essential information and are subject to recall bias. In this work, the data obtained from smartphones and integrated devices will be processed in order to identify mobility pattern changes, as they may be correlated with behavioral changes and clinical changes. For example, an increase of depressive symptoms is associated with a reduction of the patients’ physical activity [12]. Thus, patient’s mobility patterns may be used as proxies for behavioral changes. In a clinical setting, detection of mobility pattern changes could be used by clinicians or caregivers as signals of (possible) behavioral changes in their patients.

Along the lines proposed in this work, recent studies have shown that smartphone data can be used to identify behavioral changes in patients. Abdullah et al. [13] reported that combining self-reported data with data from several smartphone sensors and communication patterns resulted in reliable prediction of the Social Rhythm Metric, a clinically-validated marker of stability and rhythmicity for individuals with bipolar disorder. Another system, Monsenso, collects and extracts voice features from phone calls that were made during everyday life in naturalistic settings [14]. Concretely, the MONARCA II Research Project, which uses Monsenso, obtained 6552 numerical features related to the pitch and voice variance that were extracted from the patient’s phone calls during their everyday life. Another platform is Beiwe, which is a research-oriented platform for digital phenotyping. In [15], a method to predict schizophrenia based on anomaly detection was developed using Beiwe.

Taking into account the strengths and pitfalls of smartphone monitoring strategies, we have designed a system capable of performing continuous monitoring of patients using the smartphone’s and/or wearable’s sensors and data entry (data from phone calls, messages, ...). This platform, the Evidence Based Behavior (eB2) platform, is composed by a smartphone app, which collects these data, and a back-end server, which stores and processes them. The eB2 app collects data from inertial sensors, physical activity, phone calls and message logs, app usage, nearby Bluetooth and Wi-Fi connections, and location. Also, using Google Play Services, the app is able to access detailed activity information and nearby location data. Additionally, wearable devices provide information like the body temperature, the heart rate, or the galvanic skin response. The app was developed to run in background and the user only interacts with the app for the initial configuration. Moreover, it was designed with battery safe considerations like non-continuous recording schedule, automatic sleep/wake function, and it additionally notifies the operating system to relaunch itself when it was closed or stopped due to user’s actions or failures/reboots.

Hypothesis and principal objective

Our hypothesis was that it is feasible to develop an analysis method capable of detecting mobility pattern changes based on the data acquired by the eB2 system. Moreover, we believed that these changes may serve as proxies for behavioral changes. This study was aimed to assess the feasibility of detecting mobility pattern changes in a sample of outpatients using a smartphone application and an unsupervised detection method, which was run on a back-end server.
Methods

We performed an unsupervised detection method and a qualitative analysis on a sample of five patients out of thirty-eight outpatients enrolled in the eB2 study between April 6th, 2017 and December 14th, 2017. The eB2 study was (and still is) a two-year, multi-center-controlled trial conducted by the Fundación Jimenez Díaz. Concretely, it was a prospective study that aims to determine whether the behavioral changes detected by the eB2 system are related to any clinical change. Note, however, that in this preliminary work we only focused on mobility pattern changes.

Participants

Patients that received psychiatric care in an outpatient mental health center of the Psychiatry Department at the Fundación Jiménez Díaz, a University Hospital in Madrid, Spain, were approached to participate in this study. This department is part of the National Health Service and provides medical coverage financed by taxes to a catchment area of 420,000 people. The research was in compliance with the Code of Ethics of the World Medical Association (Declaration of Helsinki).

Patient inclusion and exclusion criteria

Inclusion criteria for this study the were either male or female outpatients aged 18 or older, diagnosed with mood disorders (ICD-10 codes F30-F39) or adjustment disorders (ICD-10 code F43.2), coding with depression. Moreover, the patients had to own a smartphone with an Android or iOS operating system, be connected to a Wi-Fi network at least once a week, and had to have given written informed consent for the eB2 study. Participants were excluded if they were under the age of 18, illiterate, enrolled in other trials, or were in situations that did not allow obtaining written informed consent. Participants were not paid. Members of the study office (EBG, MLB, RC) established an initial list of patients that meet the inclusion criteria. The contents of the monitoring interviews were reviewed to identify patients that had attended at least two appointments. These criteria yielded the aforementioned thirty-eight outpatients.

Research protocol

The eB2 app was downloaded on the patient’s smartphone the day of recruitment and configured with the assistance of the physician (see Figure 1). The app remained running in background in the patient’s smartphone during participation in the study. As previously pointed out, the app was designed with no patient interface, i.e., no action of the patient was required to capture data.
The eB2 app collected the following data: actigraphy, GPS location, Google location, app usage log, phone calls and message logs, nearby Wi-Fi and Bluetooth devices, and inertial measurement unit signals. The data gathered by the eB2 app was anonymized if it was sensitive data (position, phone numbers, ...), then it was translated to a unique data schema and finally transmitted via Wi-Fi to the eB2 back-end server where it was stored. The transmission was done through a RESTful API, which had been developed using the JAVA Spring framework. This API is SSL protected and, in order to restrict access to the patients’ information, a token-based access policy was implemented following the OAuth2 standard.

In addition to the data captured by the smartphone app, it was possible to collect data provided by third-party APIs, which were also translated into the common data schema by a service that ran at the server. The authorization to use these APIs was requested from the smartphone app and was also token-based. Additionally, data from wearable devices, like Fitbit or Microsoft Band 2, could also be uploaded. It is important to point out that, in this study, only the GPS location was used, which resulted in a simple technique and allowed for an easy clinical interpretation. Finally, signal processing and machine learning algorithms treated the acquired data to extract information, which was used afterwards by the clinicians.
Baseline characteristics

Baseline characteristics were recorded during an in-person interview for the thirty-eight patients enrolled in the eB2 study. Variables collected for each patient profile were sex, age, PHQ-9 questionnaire score [16] (see supplementary material) diagnosis and treatment. Clinical diagnoses were made by psychiatrists and were coded according to the ICD-10 for mental disorders. Moreover, in each appointment the psychiatrist administered the PHQ-9 questionnaire, which was designed to assess depression. These variables were entered manually into a secured electronic health record. Each patient was identified by a numeric code to ensure patient anonymity. This code was stored in the database and remained the same throughout all contact with the patients. This study did not include a control group.

Outcome measures

The principal outcome measure of this work was the identification of changes in the patient’s mobility patterns based on the smartphone’s sensors data, which were processed by an unsupervised detection technique. We postulated that these changes could correlate with behavioral changes and/or relapses. That is, the mobility patterns changes were proxies for the (more general) behavioral changes. These data were interpreted for each selected patient in the light of the clinical data gathered in routine appointments during study participation.

Description of the unsupervised detection technique

The proposed unsupervised detection technique was composed of two algorithms. The first one was an unsupervised clustering technique that defined types of days. This classification was done according to the mobility profile, which was also learned in an unsupervised fashion. The mobility profiles could show, for instance, that the patient was more active in the morning, in the afternoon, or in the evening or even not active at all. The first step of the clustering technique was to summarize the measured distance acquired on an interval of a few minutes into larger one-hour intervals and then the aggregated distances were stacked into 24-dimensional vectors. That is, each of these vectors corresponded to a given day, and each component was the cumulative distance traveled by the patient in the corresponding hour. Once we had these vectors, a clustering technique based on a mixture of Gaussians [17] was applied. The parameters of the model, i.e., the means and the covariance matrices (which we assumed diagonal with only two different values out of the 24 possible) were estimated using the Expectation-Maximization (EM) algorithm [17]. In particular, the estimated mean of each cluster defined what we called mobility profile as it showed that in the corresponding cluster the patient was more active (traveled more distance during the day, night or at commuting hours, ...). Additionally, the EM algorithm also allowed the handling of missing data, which corresponded to hours for which location data was not available. The final comment regarding the clustering step is the selection of the number of clusters. That is, the allowed number of different profiles (or types of days). This selection obviously depended on the amount of available data, i.e., more data allowed the technique to properly learn more profiles. However, an incorrect choice (too large or too small) would result in poor performance. For this reason, we used an automatic method, which was based on the minimum description length (MDL) criterion [17].

Regardless of whether the patient was stable or not, these profiles were likely to change from day to day due to weekends or public holidays. Hence, to detect the mobility pattern changes, it did not suffice to detect profile changes (from one type of day or
cluster to another). Concretely, we needed to detect changes in the distribution of these profiles. As an example, for a stable patient the most likely profile was that of a work day, and a different profile could have appeared for the weekends. Nevertheless, the transition from one to another was not identified as a change. What we had to detect was, for instance, if these work day profiles started to appear less often because the patient stopped going to his/her work. Hence, we applied a change-point detection technique to identify when the probability (portion of time) of each type of day suddenly changed. Moreover, this change-point detector was also able to handle missing data. Then, the clustering technique handled missing hours and the change-point detector handled missing days.

The technique described so far only exploited information given by the traveled distance, but both the technique and the eB2 system may be generalized to incorporate other kinds of data. For instance, we may exploit how many phone calls were done every hour and, similar to the distance traveled profiles, we should detect changes in the distribution of these calls. Nevertheless, in this preliminary study, we wanted to study the feasibility of this detection based only on the traveled distance as it resulted in a simple technique that was easier to interpret.

Results

Summary of the results
The patient selection process of the case series is presented in Figure 2. Thirty-eight patients were recruited in the eB2 study when we started the patient selection process for this case series. Nevertheless, out of these thirty-eight patients, only eighteen had enabled the location (GPS), and out of these eighteen, only nine had the location enabled for more than one month, which was approximately the required time for the technique to work properly. That is, during the study many patients disabled the location.
Nine patients were addressed for eligibility. The results for the nine patients are summarized in Table 1, which shows the number of monitored days (NMD), number of profiles (NP) or clusters, the number of detected change points (NCPs), the number of days between change points (DBCPs), and the phone model and OS version (PM).

<table>
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<th>NMD</th>
<th>NP</th>
<th>NCPs</th>
<th>DBCPs</th>
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<td>5</td>
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<td>1</td>
<td>154 79</td>
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<td>49 26</td>
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<tr>
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<td>4</td>
<td>1</td>
<td>37 118</td>
<td>Sony Xperia M5 - 6.0</td>
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<tr>
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</tbody>
</table>

*Patient not presented in the case series.

Table 1 Statistics of the patients addressed for eligibility.

In the following, to shed some light on the technique and the results, we present more detailed results for Patients A-E as a case series, which were the patients for which the PHQ-9 questionnaire was administered during routine appointments.
Detailed analysis for five selected patients

**Patient A** was a 56 years old woman. She was diagnosed with recurrent depressive disorder and fibromyalgia. She was prescribed a daily oral medication of Duloxetine 90 mg, Quetiapine 150 mg, Pregabalin 300 mg and Zolpidem 10 mg. She had regular bedtime and wake-up times during the study participation. The clinical assessment of depression showed high scores of PHQ-9: 21 on April 6th and 25 on May 31st. Unfortunately, this woman dropped out of medical follow-up and there are no more clinical assessments.

She participated in the study from April 6th, 2017 to February 28th, 2018 and owned a Samsung Galaxy S7 that ran Android 6.0.1. Figure 3 shows that the MDL criterion selected 8 different clusters (i.e., types of days or mobility patterns). We plot the patient's inferred mobility patterns (in logarithmic scale), which are given by the mean of each cluster. For instance, Profile 5 corresponded to a more active day and, on the days associated to this profile, the patient was more active between 9:00 and 16:00. Moreover, some of these profiles reported similar activity variations through the day. The sleep period was identified by the decrease of activity between 1:00 and 6:00.

![Distance traveled profiles of patient A.](image)

The output of the second step of the proposed method, the change-point detector, is shown in Figure 4. This figure displays the dates of the change points (upper figure) and the classification of each day given by the clustering technique and its temporal evolution (lower figure). The algorithm identified a few dates as mobility pattern changes. Concretely, there are changes on April 26th, May 31st, August 19th, September 3rd, October 27th, and November 5th. These changes appeared when the probability (portion of time) of each type of day varied.

Finally, we must point out that in Figure 4, where the temporal evolution of the types of days is shown, there are vertical light-blue rectangles, which indicate that the data corresponding to the marked days were completely missing. Even in these cases, the technique was robust enough to work properly.
Patient B was a 45 years old woman. She was diagnosed with dysthymia and prescribed a daily oral medication of Sertraline 100 mg. The clinical assessment of depression showed a clinical improvement of depressive symptoms (June 7th: PHQ-9 = 20 July 5th: PHQ-9 = 8). Overall, medical records showed an improvement during follow-up, explained by the participant as an improvement in cognitive performance, decrease of death thoughts, and improvement of hedonic capacity. She participated in the study from June 7th, 2017 to January 30th, 2018 and owned a Samsung Galaxy A5 running Android 6.0.1. In this case, the technique selected 5 different clusters and the patient’s average mobility patterns can be found in Figure 5. Figure 6 shows that our technique did not identify any change and that Profile 4 was the most common one, which was a low mobility profile (there was not a single hour with more than 1 km). In this particular patient, clinical changes had no correlation with mobility as main symptoms were expressed in cognitive and hedonic areas.
Patient C was a 40 years old woman. She was diagnosed with a moderate depressive episode. She was prescribed a daily oral medication of Paroxetine 20 mg changed to Vortioxetine 10 mg in August due to the lack of improvement. Medical records showed an improvement after the change to Vortioxetine.

This patient participated in the study from June 9th, 2017 to February 28th, 2018 and owned a Samsung Galaxy A5 that ran Android 7.0. In this case, the technique only considered four different types of days. Figure 7 shows the average distance traveled in each cluster, where we saw that the patient was more active after 7:00 in three out of the four profiles. Moreover, the remaining profile, Profile 2, showed an increased activity during the night and Profile 4 corresponded to a low mobility profile. In Figure 8, the change-point detection algorithm detected only one change on December 9th. After this date the low-mobility profile began to appear more often, which possibly indicated a decrease of the patient’s physical activity.

Clinical assessment of depression showed a decrease in depressive symptoms during follow-up period (June 9th: PHQ-9 = 22, Sept 9th: PHQ-9 = 5, December 1st: PHQ-9 = 4). Clinical improvement was associated with improved sleep time and sleep quality. A change of her work location led to less commuting, which can also explain the observed mobility patterns.
Patient D was a 36-year-old man. He was diagnosed with recurrent depressive disorder and prescribed a daily oral medication of Venlafaxine Retard 150 mg and Lamotrigine 100 mg. He was included in the study after psychiatric hospitalization discharge, and in successive appointments in outpatient setting, clinical and functional remissions were observed. Clinical assessment of depression showed minor clinical improvement (March 17th: PHQ-9 = 6, April 20th: PHQ-9 = 2, May 24th: PHQ-9 = 2, and June 26th: PHQ-9 = 0).

He participated in the study from April 6th, 2017 to August 11th, 2017 and owned a Samsung Galaxy J7 running Android 6.0.1. Figure 9 shows that the number of profiles selected by the MDL criterion was 4. As we can see Profiles 1, 3, and 4 corresponded to typical urban mobility profiles. Some showed a higher mobility during day or night and some had peaks at commuting times (7AM and 7PM). However, Profile 2 corresponded very likely to a trip as the average movement per hour was around 100 Km. Figure 10
shows the results of the change-point detector, which did not detect any change point. This is coherent with the clinical evolution of the patient.

![Figure 9 Distance traveled profiles of patient D.](image)

**Figure 9 Distance traveled profiles of patient D.**

**Figure 10 Representation of mobility pattern changes (above) identified by the technique and corresponding patterns (down) during study participation of patient D.**

**Patient E** was a 42-year-old woman diagnosed with adjustment disorder with depressed mood and lumbar stenosis. She was prescribed an oral daily medication of Escitalopram 15 mg, Pregabalin 150 mg and Ketazolam 15 mg, besides antialgic medication. Fluctuations in mood level were observed during follow-up in relation to back pain exacerbation.

This patient participated in the study from October 11th, 2017 to December 21st, 2017 and owned a BQ Aquaris M5 that ran Android 6.0.1. This patient also showed an improvement in depression scores during study participation (June 23rd: PHQ-9 = 10, October 5th: PHQ-9 = 6). In this case, as Figure 11 shows, the MDL criterion only selected 3 profiles since the amount of data was rather small and, otherwise, would very likely
have resulted in overfitting. As we can see, 2 profiles corresponded to activity during daytime, while Profile 2 showed activity evenly distributed during the whole day. As can be seen in Figure 12, the technique identified one change point on November 25th, 2017. Interestingly, this change point appeared when Profile 2 disappeared. The change point coincided with an increase of painful osteoarticular symptoms.

Discussion

Principal outcome

Our study showed that the eB2 system was capable of identifying mobility pattern changes, which may be used as proxies for behavioral changes and relapses. The technique was composed by two parts: A clustering algorithm to learn mobility profiles,
which was based on a mixture of Gaussians model and a change-point detector to identify probability changes of the mobility patterns. It is important to point out that detecting changes from one type of day to another does not suffice, what matters are the probability changes. The reason being that we could have a type of day given by a typical workday and another one given by a typical weekend day, however the change from the former to the latter (or vice versa) should not have been identified as a mobility pattern change.

This pilot study showed that the proposed technique could aid clinicians to detect relapses and other clinical changes. However, before its use in a clinical setting, the changes identified by the algorithm need to be interpreted. In this paper, we have shown the results from a few selected cases that may illustrate the potential applications of the eB2 system in outpatient follow-up of patients with depressive disorders.

The (possible) behavioral changes identification technique proposed in this work was based on the unsupervised processing of data from smartphone sensors. In particular, this work focused on detecting mobility pattern changes, which could be used as indicators of behavioral changes, and only exploited the GPS location data. The reasons were twofold: 1) it yielded a relatively simple algorithm and 2) it admitted an easy clinical interpretation (more or less related to physical activity). However, as we have previously pointed out, the platform captured much more data, and the technique can be adapted to also exploit these additional data.

Our final goal would be the identification of more general behavioral changes (online social interaction, ...) in outpatients, which has important applications for a wide range of chronic conditions, including mental health disorders. Apart from the continuous assessment of bio-parameters themselves, smartphone-based monitoring would also allow researchers to gather information on context and environment, which may prove valuable for the interpretation of the monitored biomedical data (e.g., information about weather conditions) and allow for a better interpretation of the changes.

Clinical contextualization of smartphone data
When the changes identified by eB2 were contextualized in a given patient’s routine, we were able to extract valuable information related to clinical changes. Thus, in our 5 selected patients we identified different profiles of activity.

Interestingly, changes and different profiles represented different clinical scenarios. For instance, patients B and D showed no changes, whereas for patient A, the changes corresponded to a worsening. The algorithm detected this worsening on April 26th when the PHQ-9 depression score increased between April 6th and May 31st. This participant did not show up for follow-up in September, although she continued using the eB2 app and we cannot therefore establish clinical correlations from then on. Incidentally, a change point has been detected on September 1st, which may be related to the drop-out from the follow-up. In patient D, the absence of changes reflected minimal clinical changes and stability in symptoms. However, patient B was an example in which mobility patterns were not useful for clinical purposes since the proposed method did not identify any change but there was indeed a clinical improvement. In this particular patient, the remaining data collected by the smartphone might be more useful, but this analysis is out of the scope of this work.
Additionally, changes could represent both improvement and worsening, depending on the specific patient. On one hand, the change identified on December 9th for patient C corresponded to a clinical improvement due to the disappearance of increased activity during the night from that date onwards, reflecting a better night’s sleep. In addition, a profile with low activity started to appear more often and, in fact, at this moment the patient started to have a quiet life style. In contrast, for patient E a change represented a clinical worsening due to the emergence of a profile of less activity and the disappearance of a profile of daytime activity. Both the emergence and disappearance of the above profiles indicated the worsening of the patient’s condition due to the exacerbation of her back pain.

Overall, these results highlighted that apps, such as eB2, can be used for a personalized psychiatry and that we are witnessing a paradigm shift from the traditional identification of shared factors in mental illnesses to individual and unique characteristics for each patient, i.e., personalized medicine. Ecological momentary assessment was presented as the future of outpatient follow-up [18]. However, this technique strongly relied on patient’s participation and was therefore prone to missing data [19].

Limitations
This study was conducted on a limited sample of patients with a limited time scale. Thus, it did not allow for the complete identification of ADLs, only mobility patterns could be identified. Additionally, we did not have access to an ecological self-reported description of the patients’ behavior. Ecological data are usually based on self-assessments, and provide information that may be correlated with the digital phenotyping [19]. Ideally, we should have combined self-reported ecological data capture [20] with the results obtained by the eB2 system to test whether the automatically detected changes correlated with the clinically diagnosed changes or data ecologically reported by the patient. In this study, the algorithm detected changes in mobility patterns, which could be identified as behavioral changes. However, in this explanatory setting, we were not able to completely determine whether these behavioral changes identified by the algorithm corresponded to a clinical modification or the emergence of any normal or abnormal behavior. We also identified several factors that may explain the changes, and that were not related to any modification in depressive symptoms. Additionally, this study was based only on GPS data and many patients disabled this sensor. This is a problem that we will need to address in the future, and it is therefore important to convince the patients to not disable the location in their smartphones. Nonetheless, location is not the only source of information, albeit it is important, and we should consider other types of data in future studies.

Data privacy is a serious concern in the e-health research area. The eB2 app captured data from smartphones, which possibly was a deterrent for patients to accept the app [21]. However, the selected patients were aware of the general approach of our method and were not very concerned about sharing their personal data since it was anonymized at the smartphone. Another major concern regarding personal electronic data is data security [22]. In order to preserve the patient’s privacy and reduce the risk associated to a non-legitimate access, all the sensible information stored in the eB2 server was hashed and anonymized. Concretely, phone numbers, email addresses, Bluetooth, and Wi-Fi MAC addresses were hashed using the SHA-1 algorithm and the location was transformed using a non-invertible function. Specifically, we stored randomly-rotated relative location
coordinates, where the origin was the location that was most common during the first three days after installation (typically the patient’s home). Our app was (and still is) available via app stores, such as Google Play or App Store, which allowed us to continuously update and improve the app based on newly discovered bugs and also user feedback. For instance, we have improved the battery consumption, which should improve patient adherence in the future.

Future application
Smartphone-based systems for managing and monitoring behavior present a highly promising field of innovation in health care. The normal use of a smartphone on a daily basis generates a larger amount of data than the amount that is typically collected in questionnaire-based studies or online interventions, but it requires that the patient carries his/her smartphone most of the time. Smartphone sensor-based analysis already showed interesting results in the assessment of bipolar disorder [13], depression symptoms [8], prediction of schizophrenia [15], and sleep duration [23]. This work is in line with recent proposals of Torous et al., which established digital phenotyping as a promising method in the assessment of patients with mental health conditions [24].

We proposed a preliminary assessment of a method for patients with mental health conditions. Our system was able to identify changes in the mobility patterns of outpatients, which may correlate with behavioral changes and relapses. In the future, eB2 may also be used for the assessment of physical activity in therapeutic programs or for the identification of ADLs in the elderly [6].

Conclusion
We have developed a system that is able to capture data from the smartphone’s native sensors and other wearables. The eB2 system is composed by a smartphone app and a back-end server. The preliminary results of the ongoing eB2 study showed the feasibility of an unsupervised detection method for detecting mobility pattern changes, which we considered proxies for behavioral changes, in outpatients by exploiting the data acquired by the eB2 app. So far, only location data was used, which resulted in relatively simple processing techniques and allowed for an easy clinical interpretation of the results. Additionally, it is important to point out that this method did not need intervention from the patient. However, it was crucial that the patient carried his/her phone all the time. With the development of the eB2 system, we aimed to address most challenges raised by e-health technologies in ecological monitoring.
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