Monitoring activity of patients with bipolar disorder using smart phones

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ABSTRACT

Mobile computing is changing the landscape of clinical monitoring and self-monitoring. One of the major impacts will be in healthcare, where increase in number of sensing modalities is providing more and more information on the state of overall wellbeing, behaviour and health. There are numerous applications of mobile computing that range from wellbeing applications, such as physical fitness, stress or burnout up to applications that target mental disorders including bipolar disorder. Use of information provided by mobile computing devices can track the state of the subjects and also allow for experience sampling in order to gather subjective information. This paper reports on the results obtained from a medical trial with monitoring of bipolar disorder patients and how the episodes of the diseases correlate to the analysis of the data sampled from mobile phone acting as a monitoring device.

Categories and Subject Descriptors

C.5.3 [**Computer System Implementation**]: Personal Computers

General Terms

Algorithms, Measurement, Experimentation, Human Factors.

Keywords

Activity patterns, physical activity levels, personalised monitoring, mobile computing, mental health, depression, bipolar disorder.

1. INTRODUCTION

Technological advancements in mobile computing have had a major impact on a number of disciplines including lifestyle monitoring, fitness, behaviour change; up to scientific disciplines, including medicine. These advancements, including miniaturisation of embedded sensor platforms have enabled monitoring of wide aspects of human behaviour, inlcuding capability of recognizing activities and inferring behaviour patterns. As a result, there is an increase in accuracy of measurements of various physiological parameters through sensing, processing and monitoring of various vital signs that can assist people towards positive behaviour change and their health management [1], [2], [3].

Advancements in sensor technology, have found their way inside mobile devices, becoming an integral part of them. Considering the popularity of mobile devices, new possibilities are opening up, those of monitoring subjects outside the laboratory, in unconstrained and uncontrolled environments so as to capture subjects' natural behaviour. Possibilities of sensing outside the lab are numerous, ranging from lifestyle monitoring, fitness behaviour change, detecting stress and burnout in workers, up to applications in medicine, including monitoring of patients with major depression and bipolar disorder.

Mobile computing can have a substantial impact in monitoring patients with mental disorders due to the following factors:

i) symptoms of mental disorders are primarily manifested through changes in patients' behaviour. For example depression is manifested through motor retardation, where such change in behaviour can be captured through analysis of the information from the motion sensors on the mobile phone; and

ii) psychiatric assessment of mental disorders is typically carried out through the use of a questionnaire. The questionnaire relies on patients recalling events pertaining to their past behaviour, such as amount of physical activity for example reported by the patient. Self-reporting suffers from a number of issues, including: a) *recall bias*; where subjects have difficulties recalling events in the past; b) *subjectivity*; self-reporting may be affected by the current mental state of the subject; and c) *high effort*; self-reporting requires high effort in order to gather high quality data, especially in longitudinal studies, where data is gathered either through self-reporting or through a third party observer.

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Mobile computing can address these difficulties through continuous monitoring of user activities, by sampling sensors commonly found on mobile devices and in return providing objective measures of behaviour phenomena. Naturally, mobile devices also allow for experience sampling through self-reporting. Continuous monitoring is especially suitable for measuring physical activity, since activity levels of subjects can be measured through the phone's accelerometer and a solid picture of overall physical levels can be inferred. Measuring physical activity levels in this manner alleviates the issues faced when relying on subjects' memory of physical activity events, which is the current practice in psychiatry.

Considering advantages of using mobile computing to monitor human behaviour, this paper presents results of a medical trial, where patients with bipolar disorder used smart phones equipped with an application that was capable of continuously sampling all the available sensors on the phone. The trial lasted for a period of three months, during which, diverse behaviour aspects of patients were measured, including their physical activity levels, location patterns, time spent inside and outside their home and clinic, sleep patterns and social activity levels. The patients were fully unconstrained in terms of placement of phone and its use. They used the phone in the usual manner, where there were instances when the phone was forgotten or not used for a period of time, as shown by the sensors logs. In terms of analysis of sensor data, this paper reports on the measured physical activity levels through a smart phone, during the trial and how these levels correlate with the disorder episodes.

2. RELATED WORK

2.1 Monitoring human behaviour through mobile computing

Large research body has shown the potential of monitoring human behaviour using mobile computing and sensing technologies. Besides the powerful sensing capabilities for monitoring people's behaviour, there exists a personal relationship with the mobile phone that makes it an ideal candidate to record human behaviour with as high fidelity as possible to natural behaviour.

Studies have shown the effect of the use of mobile phone for supporting regular physical activity, which is of critical importance in reducing the risks of several chronic diseases. The study at [4] shows how sedentary behaviour presents several threats to people's health of different ages, which can be reduced through encouragement to engage in regular physical exercise. The use of sensors in mobile computing to record heart rate and heart rate variability provide sufficient information to analyse and infer users' fitness level and progress. Providing a virtual trainer on the mobile phone has shown to encourage users to go outdoors perform physical activity. In this line, the work at [5] namely UbiFit Gardens, targets adults who want to increase their physical activity. This study provides an automatic recording of walking, running, cycling and also shows how self-monitoring can provide functionality for the users to document their physical activity and aid in exercise routines.

Another aspect of user behaviour that is indicative of overall wellbeing and health is sleep quality. Sleep monitoring can be used to detect a number of sleep disorders, including sleep apneas, which often go undiagnosed. Thus, a number of technologies have been designed to promote healthy sleep, including work of Choe et al. [6] that have identified design opportunities for using mobile phone to support healthy sleep behaviours. The authors emphasized the importance of monitoring sleep in ways that are unobtrusive and fit with people's everyday lives. Similarly, in [7] authors demonstrate the potential of monitoring sleep apnea while measuring breathing and moving patterns using embedded microphone and accelerometer in mobile phones. In addition to behavioural patterns monitoring at work, Tentori et al. [8] conducted a study to understand the way clinicians monitor and assess patients activities. With a use of mobile phone they were able to identify patient's needs by monitoring activities executed by patients. In similar line, Hansen et al. [9] have demonstrated the benefits of using mobile phones, namely "AwarePhone" system which can support context aware communication for clinicians in a surgical ward. The system tracks clinicians in selected areas and the use of mobile phone allows clinicians to enrich communication between health-care workers. The research body presented in this section shows the potential of mobile computing and embedded sensing capabilities, not only to monitor aspects of human behaviour, but also to infer the overall state of the users.

2.2 Mobile computing in medicine

Prevalence of chronic diseases is increasing all over the world and management of diseases represents one of the greatest health care challenges. As such, monitoring devices have the potential to support patients with chronic diseases through monitoring of their health aspects. Mobile computing and sensing technologies have shown this potential to improve healthcare quality, efficiency and reduce care costs.

Work carried out in [1], [10], [11], [12] has focused on recognition and treatment of mood disorders in the field of psychiatry, utilizing technological solutions to tackle mental health issues. Compared with standard clinical practice for monitoring patients, measurements rely on observation data collected in laboratory setting or in person. For example, in [13] authors argue that increased knowledge about motor activity and repetitive movements of bipolar disorder patients during the manic episodes offers deeper insight towards new therapies. Therefore, accurate and continuous monitoring has become increasingly important in healthcare, where employing technology for patient monitoring can help assess the impact of mental illness on a patients daily activities and increase effectiveness in treating the mental disorder [1], [10], [11]. Equipped with powerful embedded sensors, smartphones have become capable of monitoring multiple dimensions of human behavior, including physical, mental, and social interaction dimensions [3], [12], [4], [14] [32].

A number of research activities have demonstrated the use of mobile phone applications allowing physicians to monitor patients with chronic heart failure [2] and detect early signs of arrhythmia that can indicate an imminent heart attack. The authors reported the feasibility of a new wireless telemonitoring system via a mobile phone. Furthermore, Alexander et al. [15] have shown the importance of using mobile phone monitoring patients with hypertension. The authors emphasize the importance of remote monitoring of vital parameters to diagnose health problems and provide early warning signals of potentially dangerous changes in patients' health status of patients with hypertension. Using mobile devices have shown significant improvement for blood pressure measurement.

Simpson et al. [16] applied self-monitoring among alcohol use disorder patients in early recovery based on Interactive Voice Response (IVR) on mobile phones. The patients reported the positive effects of monitoring on urges to use alcohol and posttraumatic stress disorder symptoms.

Rapid improvements in mobile technologies are also facilitating involvement of psychiatry for monitoring patient's mental health. Mobile application "Optimism App" [17] designed to monitor depression, has been developed for patients to log self-reported mood, activities including exercises and quality of sleep. Providing feedback about their health status to the patients, it was highly recommended by psychiatrists to use in monitoring the patients' mental health.

However, despite the improvements of mobile technology, very few solutions implemented in clinical practice for ambulatory monitoring of patients with bipolar disease. The work at MIT and Massachusetts General Hospital [18] was designed to monitor depression using LiveNet system. The patients were carrying the mobile physiological sensing technology to track depression symptoms and objectively measure them. The authors emphasized the importance of validating electro-convulsive therapy (ECT), which resulted with positive effects on patient's depressive state.

Assessing the activities of daily living is very often emphasized as an important aspect in order to understand progress of bipolar disorder. Blum et al. [12], [19] stated that monitoring via a set of sensors may free bipolar disorder patients from various drawbacks. Furthermore, they investigate that the mood status related data could be reported via mobile phones as well as self-reporting in order to provide details about mental state of the patient and help set up therapeutic sessions between patients and caregivers.

Several research initiatives have focused on automatic monitoring of patients suffering from bipolar disorder [1], [14]. However these studies mostly faced issues regarding obtrusiveness. The work at PSYCHE project [20] used a smart textile platform and mobile phone to collect physiological data relevant to mental wellbeing. The authors have presented the importance of estimating the heart rate variability from respiratory rate. But such an approach may pose a discomfort in daily use caused by physiological sensors, such as ECG.

2.2.1 Physical activity monitoring

Interest in physical activity monitoring for patients with bipolar disorder is increasing. Most of the important findings associated with physical activity, have shown how physical activity reduces risk for chronic diseases, such as cardiovascular diseases [2], obesity [21], and enhance mental health with respect to lowering levels of anxiety and depression, elevating mood, improving self-esteem and reducing stress [13], [22], [23], [24], [25], [26]. For this reason, an accurate measurement of physical activity is an important component of research, in order to monitor people's health and to quantify the relation between physical activity and outcomes of chronic diseases. Furthermore, a persuasive personal monitoring system, has been suggested for management of a wide range of health-related issues [27]. These types of systems help users by enabling them to monitor and visualize their behaviours, keeping them informed about their physical states, reminding them to perform behaviours or tasks, providing feedback on the effectiveness of their behaviours, and recommending healthier behaviours or actions. Such systems can also help with the management of mental illnesses, such as bipolar disorder, while monitoring level of physical activities, sleep quality, mood and environmental factors, as significant detriments to quality of life in bipolar disorder.

Most studies utilizing self-monitoring are based on traditional monitoring with paper- and pencil diaries and questionnaires [28]. These methods are often biased assessment of the health outcomes. Due to irritable state of individuals with bipolar disorder during depressive and manic state, using traditional methods patients are prone to neglect or to overestimate performed activities. Thus, if self-assessment on the mobile phone enables easier monitoring and tracking of the patients' progress than traditional methods, then the data collected will be of higher quality. The alarm providing the reminders to fill out the form can also increase patient motivation to complete daily monitoring activities [28]. The benefits of using technology include more accurate data and also provide clinicians with the ability to evaluate the patients' progress in a more granular scale and increase the efficacy of the treatments. Moreover, bipolar patients who are trained to use self-help treatments can benefit from greater control over their care and life decisions and can detect early warning signs of serious illness [29].

Next section focuses on our monitoring approach and elaborates on the results obtained from the clinical trial.

3. PATIENT TRIAL SETUP

3.1 Bipolar Disorder

Bipolar Disorder [14] is a common and severe form of mental illness. One of its main characteristics is a repeated relapse of two polar episodes – mania and depression. Patients suffering from the disorder may experience periods of manic, normal and depressive state, often in rapid succession. The current standard for diagnosis of bipolar disorder uses subjective clinical rating scales based on self reporting that were developed in the early 1960s (e.g. HAMD, BRAMS scales) and other more recent variations of them (e.g. BSDS). While the efficacy of these scales has been proven in diagnosing bipolar disorder, they have their drawbacks, as they are a potential source of subjectivity in the diagnosis. Drug therapy is the main treatment currently offered, but its effectiveness critically depends on the timing of administration. Thus, therapy can be very effective if administered at the beginning of a patient's transition to a different state (e.g. from normal to depressive). However, it is much less so when applied only after severe symptoms have persisted for a significant time. Therefore, understanding correlation between objectively measured factors, such as physical activity, and patient state is of high importance in order to understand as early as possible an onset of an episode and provide a timely intervention.

3.2 Trial Description

A total of 9 patients were recruited, 8 female and 1 male to participate in the study. As inclusion criteria, each of the patients had to be diagnosed with bipolar disorder, categorized by the ICD-10 classification (class F31). The trial was uncontrolled, not randomized, mono-centric, prolective, observational study. Each patient was given a personal smart phone to use in any way they wanted. There were no constraints of any kind placed upon the patients, with respect to holding the phone in a specific manner or at a specific place in the body or otherwise.

The phone had the continuous sensing app installed that recorded data on the phone memory and transmitted the data periodically to a dedicated server. All sensing modalities were sampled, including microphone, accelerometer, GPS, WiFi access points, Bluetooth calls, SMS and their duration. The app, shown in Figure 1 ran continuously in the background, sampling these sensors and was set to start automatically on phone start up.

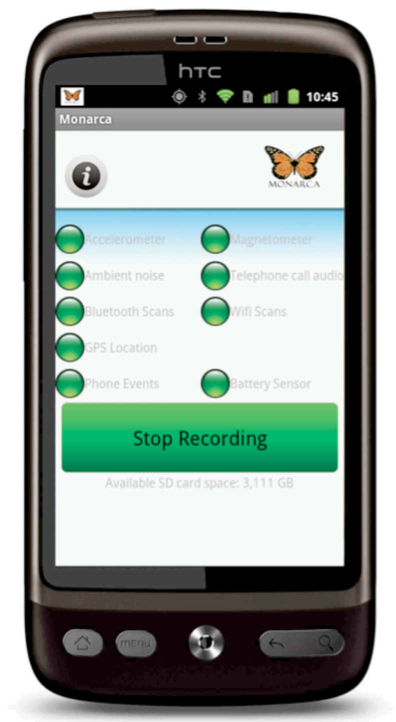

Figure 1 Patient monitoring application

Considering there were a number of sensing modalities sampled, for the purpose of this paper we focus on analyzing accelerometer data only and estimating physical activity levels of patients and how these levels correlate to the diseases.

Monitoring physical activity levels is especially important for bipolar disorder patients, since each polar episode (mania and depression) is directly manifested through activity levels; that is, depressed patients exhibit psychomotor retardation while manic patients exhibit psychomotor acceleration.

3.3 Patient state evaluation

Patient monitoring application was designed to measure two aspects, namely patients' internal affective states, through the use of questionnaires; and, objective behaviour, through sampling of phone sensors. The application has been developed in close cooperation with the psychiatrics in order to capture relevant aspects of the disease. In order to increase patients' motivation to provide daily experience sampling, the application provides alarms and reminders to fill out the questionnaire at a predefined time in the evening. Through the questionnaires the patients were able to provide their current state as well as activities they performed during the day, estimate their sleeping hours as well as quality, time spent outdoors and their social activities. However, in this study we did not use self-reported information, rather we focused on patients' evaluation by the psychiatrists.

Psychiatric assessment and the psychological tests were performed every 3 weeks over a period of 3 months at TILAK (Department of Psychiatric, State Hospital, Hall in Tyrol, Innsbruck). The schedule has been set by the psychiatrists in such manner as to reduce memory effect, which would have biased the evaluation outcome.

The clinicians used the following standard scales during the assessment of the patients:

- Hamilton Depression Scale (HAMD): HAMD scale has been applied to rate the severity of depression in patients through assessment of a range of symptoms. The higher the magnitude of symptoms, the higher is the scale of severity of depression (cut-off value: >=8)

- Young Mania Rating Scale (YRMS): YRMS is most frequently utilized rating scale to assess manic symptoms. The baseline scores can differ in general, depending on the patients' clinical features such as depression (YMRS=3) and for mania (YMRS=12).

In order to evaluate the patients, the HAMD and YRMS scores were normalised in a scale of -3 to +3 where the former indicates Severe Depression and the latter indicated Severe Mania.

Psychiatric evaluation scores of the patients are shown in Figure 2 using the normalised scale.

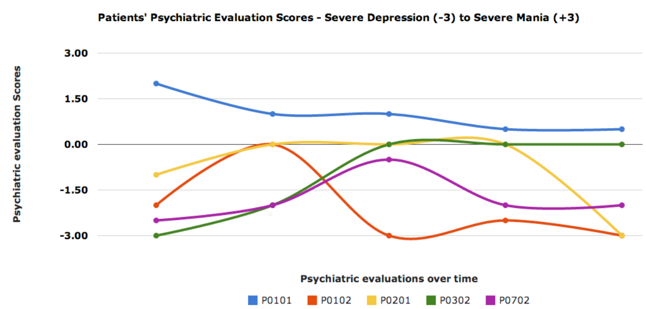

Figure 2 Normalised patients' psychiatric evaluation scores. The score of -3 indicates Severe Depression; +3 indicates Severe Mania; while, mid-graph (score 0) indicates normal state.

As shown in the Figure, patient P0101 (blue curve) experienced a severe manic episode at the initial stage and during the course of the trial returned to mild manic state. While on the other hand, patient P0302 (green curve) initially experienced severe depression and then returned to normal state. Other patients had similar patterns of change, however depressive episodes are much more prominent in these patients, which is in line with the characteristics of bipolar disorder [30].

Numerical values of the scores are shown in Table 1 where each patient had 5 psychiatric evaluations over the monitoring period of three months.

A number of challenges plagued the trial, most prominent of which was patient compliance. Considering that the trial was conducted under uncontrolled conditions, during normal daily life of the patients, it was impossible to ensure that the patients always carried the phone with them. In addition, some patients would switch off sensing application at certain occasions, creating gaps in available data, which can be seen when we present the analysis of correlation in the sections that follow.

Table 1 Numerical scores of psychiatric assessment

Patient ID	*P0101*	*P0102*	*P0201*	*P0302*	*P0702*
Psychiatric assessment scores	2.00	-2.00	-1.00	-3.00	-2.50
	1.00	0.00	0.00	-2.00	-2.00
	1.00	-3.00	0.00	0.00	-0.50
	0.50	-2.50	0.00	0.00	-2.00
	0.50	-3.00	-3.00	0.00	-2.00

As it was mentioned in the introduction section, the overall study included 9 patients. However, in this paper we focus only on patients that have shown variations on their psychiatric evaluation scores during the monitoring period. Patients that have remained depressive or manic, showing no changes in psychiatric evaluation scores, were excluded from this study, since it was unlikely to detect any changes in physical activity levels. For other patients there was not enough data available to carry out the analysis. Therefore, the results presented in this paper pertain to five patients as shown in Table 1.

3.4 Approach and Results

In order to quantify the level of activity we use accelerometer sensor data acquired from the smart phone. We have captured 3-axial linear acceleration continuously at a rate of 4Hz to 10Hz, which varied due to Android system operating conditions, such as system load and battery levels. However, this sampling rate was sufficient to infer physical activity levels of patients. The accelerometer signals were resampled at fixed rate of 5 Hz. For each patient there was an average of 2 GB of raw accelerometer data.

Physical activity levels were estimated using pre-processed accelerometer data. Acceleration magnitude vector was calculated as square root of sum of squares of individual acceleration axis, which allowed calculation of physical activity levels to be invariant to phone orientation, which due to unconstrained nature of the trial, phone orientation is unknown. The variance of the magnitude on each 128 samples provided an activity score, which was set within a threshold of three states, namely 'none', 'moderate' and 'high' activity as detailed in FUNF framework [31].

For this study we are interested in change of overall activity levels, therefore we have combined the two active states ('moderate' and 'high') to produce a single score. In the sections that follow, we provide results of our initial analysis of overall activity levels and also the results of intervals, where monitored days were divided in daily intervals.

It is important to note that for this analysis, we have excluded the days in which the patient went to the clinic for the psychiatric evaluation. This is because during the assessment there would be physical activity recorded, which may not correspond with the natural behaviour of the patient and thus would have biased our results.

3.4.1 Initial analysis

During initial analysis phase, we were interested whether overall physical activity levels show any correlation with the patients' state. Literature suggests that patients in the depressive state show decreased levels of physical activity in comparison to their normal state, while the contrary holds true for manic patients. Note that in this study we did not carry out between subjects comparison, rather we focused on differences within subject.

Table 2 shows activity levels of patients for the whole duration of monitoring of 3 months and correlation with the psychiatric evaluation scores, using Pearson correlation coefficient *r*.

Table 2 Correlation between patient state and overall physical activity levels ($p < 0.05$, N = 5)

Patient ID	*r*
P0101	**0.672**
P0102	**0.377**
P0201	**0.332**
P0302	**-0.148**
P0702	**0.290**

As it can be seen from the table, there exist a correlation between the patients' state and the overall physical activity levels. The correlation is strongest for patient P0101 ($r = 0.672$), while there is a low negative correlation for P0302 ($r = -0.148$), which indicates that the overall level of physical activity (as measured by the phone) was decreasing as the patient's state was improving (patient P0302 went from major depressive episode (-3) to a normal state (0) as shown in Figure 2).

While there have been studies that correlate overall physical activity levels with depressive and manic episodes as cited in related work section, our study did not yield strong correlation for all patients.

Considering these results, we have decided to investigate further in order to understand how the daily behaviour levels correspond to bipolar disorder episodes. In this respect, we have divided the day into four intervals, namely Morning (06 AM to 12 PM), Afternoon (12 PM to 06 PM), Evening (06 PM to 12AM) and Night (12 AM to 06 AM). Clearly, different patients will have different behaviour patterns as to what constitutes morning time, however the division of the day was setup in order to investigate whether at specific 6-hour intervals there is a higher correlation of physical activity and patient state.

3.4.2 Daily interval analysis

Once the days were divided in intervals, we investigated trends of physical activity levels in comparison to the patients' psychiatric evaluation. In order to normalize activity levels we have calculated the sum of all activity percentages in hourly basis for each day. This provides the average of activity level for each hour and each day. Separating the activities into hours allowed us to compare normalized average activity levels in different hours of the day.

Motivated by the clinical work carried out in studying bipolar disorder patients in [26], where patients in depressive state have decreased morning activity levels, we examined association between *morning* Physical Activity (PA) levels and psychiatric scores, as shown in Table 3. Mean levels of PA in the morning had a noticeable difference when patients went from a depressive state to a normal state.

This increase can be seen across all patients, although it is most noticeable for patient P0201, where the average increase in physical activity went from 16.17% during depressive state to 45.03% during normal state; and patient P0302 where the average PA increase went from 16.17% during depressive state to 45.03 % during normal state.

Table 3 Relationship between morning physical activity (PA) and psychiatric assessment scores in depressive episodes (*n/a - not applicable, since the patient did not experience a second depressive episode)

P	Nr. P.E	Avg. of PA in Depressive State (Score)	Avg. of PA in Improved State (Score)	PA Improvement factor	Avg. of PA in Depressive State	Decrease of PA
0102	**5**	12.49 % (-2)	14.42% (0)	15.45 %	6.46% (-3)	55.20%
0201	**5**	16,17 % (-1)	45,03% (0)	178,47 %	38.70 % (-3)	14.06%
0302	**5**	4.42% (-3)	12.16% (0)	175.11 %	n/a*	n/a*
0702	**3**	15.42 (-2.5)	21.93% (-0.5)	42.22 %	13.98 % (-2)	36.25%

The other two patients, P0102 and P0702 had a noticeable decrease of physical activity as they went from a normal state to a depressive state. As such there was a 55.20% decrease in physical activity levels for patient P0102 that went from normal state to severe depression (score of -3), while for patient P0702 the decrease in physical activity was 36.25% as he experienced a depressive episode with score of -2.

For the patient that experienced a manic episode, P0101 we have seen a reverse trend, similar to the study reported in [11]. The average PA decreased from 5.70% during a manic episode to 1.14% during a mild manic episode as shown in Table 4.

Table 4 Relationship between physical activity (PA) and psychiatric assessment scores in manic episode (*n/a - not applicable since the patient did not experience a decrease in the assessment score)

P	Avg. of PA in Manic State (Score)	Avg. of PA in Improved State (Score)	Improvement of PA	Decrease of PA
0101	5.70% (+2)	1.14% (+0,5)	80%	n/a

The reason that recorded activity levels were low for the manic patient can be attributed to the fact that the usage of the phone for this patient was very low; which, incidentally, is one of the symptoms of mania. This was also confirmed from the recordings of phone usage logs (provided by the application), resulting in low amount of accelerometer data that was available for analysis.

3.4.3 Correlation of physical activity during daily intervals with psychiatric assessment scores

Previous section focused on morning activity levels and their relationship with the psychiatric assessment scores. However, we also wanted to investigate whether there is a correlation between physical activity levels during other daily intervals, namely afternoon, evening, night and psychiatric evaluation scores.

In this respect we have calculated Pearson correlation coefficient between physical activity levels during each daily interval and psychiatric evaluation scores for all the patients.

Results of the correlation are shown in Table 5.

Table 5 Correlation between patients' state and physical activity level during day intervals ($p < 0.05$, N = 5, $N^{‡} = 3$)

(*n/s not statistically significant result ($p > 0.05$) - *n/d not enough data recorded, due to phone being off)

	r			
Patient ID	Morning	Afternoon	Evening	Night
P0101	n/s*	0.315	-0.045	n/d*
P0102	0.581	-0.542	**0.619**	n/d*
P0201	0.261	**0.586**	0.243	n/d*
P0302	**0.858**	-0.842	-0.627	0.604
P0702 ‡	**-0.746**	0.213	0.452	0.007

One of the interesting findings from analysing activities of these patients is that there is much stronger correlation between the individual daily intervals than there is for the overall activity levels (shown in Table 2).

These results can be seen from patient P0102 where correlation with overall activity level is r = 0.377 whereas strongest correlation with daily interval is r = 0.619 (Evening). A similar pattern emerges with other patients also, such as P0201, where the values are r = 0.332 for overall activity levels versus r = 0.586 for daily interval; P0302, with values r = -0.148 (overall) vs r = 0.858 (interval); and, P0702 with values r = 0.290 (overall) vs r = -0.746 (interval), where this patient had a strong negative correlation of physical activity levels with psychiatric scores.

One exception to this pattern is patient P0101, where correlation with overall activity levels is much higher (r = 0.672) than the correlation with daily interval (r = 0.315). Without a further study, we can only speculate on the reasons for these results. However, from the study group, this patient was the only one to have experienced a manic episode at the onset of the trial, with the state decreasing in severity towards the end of the trial (see Figure 2). One speculative explanation may be that the patient's overall activity levels may have correlated well with their state, however due to missing data for the morning and night interval, it is impossible to understand whether those intervals may have affected the overall correlation score.

4. CONCLUSION

This paper has shown the applicability of mobile computing to monitor user behaviour in general and physical activity levels of patients with bipolar disorder in particular. As current literature suggests, there exists a correlation between physical activity levels and psychiatric assessment of depression; however, one of the main findings of our study is that within our sample, correlation of physical activity levels with psychiatric assessment scores is much higher when considering specific intervals of the day, in comparison to level of physical activity for the whole day. Considering substantial variations between patients of both, overall physical activity levels and physical activity levels within daily intervals provides a clear evidence of difficulties in generalising among patients. Therefore, personalised models are better suited to detect early signs of an onset of a bipolar episode and facilitate timely intervention.

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