
SleepSight: A wearables-based relapse prevention system for Schizophrenia

Maximilian Kerz

King's College London
16 De Crespigney Park, SE5 8AF,
United Kingdom
maximilian.kerz@kcl.ac.uk

Amos Folarin

King's College London
16 De Crespigney Park, SE5 8AF,
United Kingdom
amos.folarin@kcl.ac.uk

Nicholas Meyer

King's College London
16 De Crespigney Park, SE5 8AF,
United Kingdom
nicholas.meyer@kcl.ac.uk

Mark Begale

Northwestern University
750 N Lake Shore Dr, 60611,
United States
m-begale@northwestern.edu

James MacCabe

King's College London
16 De Crespigney Park, SE5 8AF,
United Kingdom
james.maccabe@kcl.ac.uk

Richard Dobson

King's College London
16 De Crespigney Park, SE5 8AF,
United Kingdom
richard.j.dobson@kcl.ac.uk

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Abstract

SleepSight is a novel approach to detecting early signs of relapse in psychosis, thereby allowing targeted intervention for relapse prevention. The system uses a wireless-enabled wearable device and smartphone to collect longitudinal accelerometry, heart-rate, ambient light and smartphone usage patterns from patients living in their homes. These data are encrypted and sent via the mobile data network to a secure server for real-time analysis, using the Purple Robot mobile application.

This study tested feasibility and acceptability of the SleepSight system in 15 participants with a diagnosis of schizophrenia. Patient recruitment and data collection was completed in January 2016, at the South London and Maudsley NHS Foundation Trust (SLaM), the largest mental health service provider in the EU. The project is a unique multidisciplinary collaboration between the NIHR Biomedical Research Centre for Mental Health, the Institute of Psychiatry, Psychology and Neuroscience, and the National Health Service.

Author Keywords

Authors' choice; of terms; separated; by semicolons; include commas, within terms only; required.

ACM Classification Keywords

Human information processing; Web-based services; Input devices and strategies; User-centered design;

Introduction

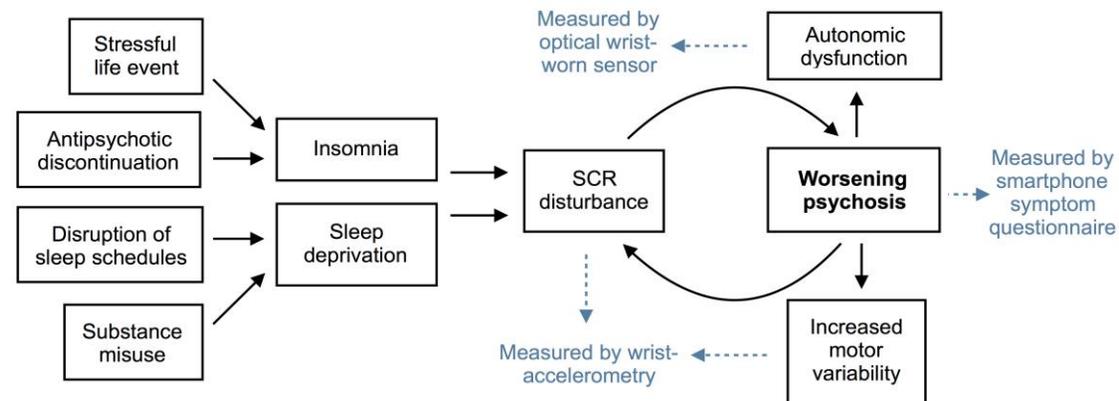
Schizophrenia manifests itself as positive symptoms, including delusions, hallucinations and thought disorder as well as negative symptoms, including abnormal social behaviour and withdrawal. Therapeutic treatments often require an initial phase of dose adjustment to take effect and may result in a loss of drug efficacy, requiring dose readjustment with disease progression (Eisner, 2013). Around 80% of those treated for a first episode of psychosis relapse within five years (Robinson et al., 1999). This is partly due to limitations with self-reports, questionnaires and fortnightly or monthly screening as intervention measures in community based patients.

Early signs of relapse in Schizophrenia Most relapse prevention strategies rely on self or observer-rated

early warning signs (EWS) such as anxiety, dysphoria, and poor concentration that manifest prior to relapse (Eisner et al 2013). However, sensitivity and specificity have been modest, and are limited by infrequent assessment and loss of insight. Objective, physiological markers which can be sampled continuously are likely to have greater precision, place less burden on the user and thereby improve adherence, and allow passive monitoring to continue even once insight has been lost (Figure 1).

In clinical practice, disturbance in normally rhythmically organised behaviours such as the sleep-wake cycle and activity and arousal levels are frequently observed in individuals presenting during relapse, and are cited in retrospect by patients and their carers as precursors to relapse (e.g. Herz et al 1980). Such disturbances are now readily measurable using accelerometers and optical heart-rate monitors embedded in wearable and mobile technologies, and may serve as clinically useful early indicators of relapse.

Figure 1: A flowchart showing the consequences of insomnia and sleep deprivation, namely a progressively worsening psychosis in Schizophrenia patients. Using wearable devices and smartphone, this effect can be passively monitored and fed back to clinicians and care-teams.



The PANSS

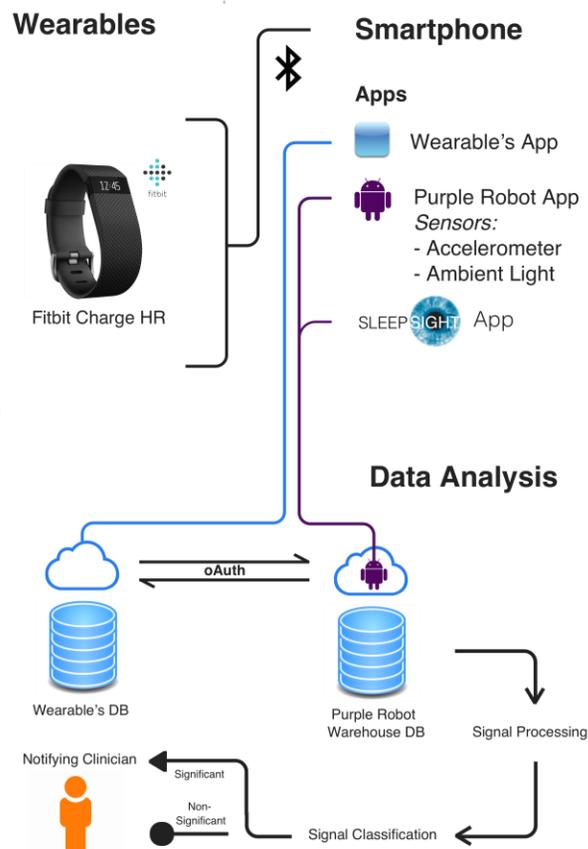
The positive and negative symptom scale (PANSS) is used to measure symptom severity in patients with Schizophrenia. The scale was introduced in 1987 and is now a widely used tool in the realm of antipsychotic therapy.

Figure 2: The flowchart depicts the information flow between the different components of the SleepSight platform. The Fitbit Charge HR is transmitting its data to the smartphone (Nexus 5) via Bluetooth (BLE), from where it is uploaded to Fitbit's servers. Accelerometer and light data as well as daily questionnaire submissions from the SleepSight app are directly uploaded to our KCL server from PurpleRobot. Once all data had been acquired, signal processing and anomaly detection was employed to identify a change in behavior within each participant. Ideally, this will lead to notifying a clinician, who can intervene before the participant enters a relapse event.

Methodology

Study design

The study involved the recruitment of 16 participants all of whom suffered from Schizophrenia. Each participant was given a smartphone (Nexus 5) as well as a wearable device (Fitbit Charge HR) and was monitored for a period of 8 weeks.



Data acquisition

The Purple Robot framework, developed by the Centre for Behavioural Intervention Technology (CBITS) at Northwestern University, provides an interface to on-board mobile phone probes (e.g. gps, light, temperature) and a framework for integrating other mobile-aware probes e.g. wearables featuring accelerometers, oxygen saturation, heart rate, blood pressure, blood glucose. Using this platform, we have built a framework to enable patient reported outcome (PROM) data from smartphone applications, smartphone sensors and other sensor devices to be collected and analysed.

The SleepSight platform

The SleepSight platform was developed with the design criteria of device-agnosticism, reliability and user-acceptance in mind (Figure 2). As a result we decided to utilise the Fitbit Charge HR, featuring an optical heart rate sensor and accelerometer, as a wearable. The Nexus 5 had the Purple Robot and Fitbit mobile app installed to upload their data to our secure King's College London (KCL) and Fitbit's server, respectively. Additionally, the phone featured a proprietary SleepSight app which would ask the participant to submit a sleep diary and PANSS-like questionnaire on a daily basis. The questionnaire data was used to complement the passively collected data set as labels.

Finally, once the data arrived on our KCL server, we employed a probabilistic model to detect anomalies in each participant's behavior, individually.

Data analysis

There are many ways to disseminate valuable information from a multivariate high resolution time

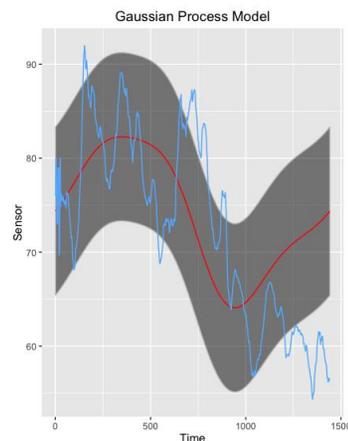


Figure 3: The plot depicts a Gaussian Process (grey band) trained on a participant's heart rate time series (TS) on days with a low symptom score. The model is fitted over the entire day starting with wake time and ending with sleep, characterised by a lower heart rate. A smoothed heart rate TS from the test set is fitted on top of the model (blue curve) and the residual error is used to detect anomalies within this particular sample TS.

Figure 4: The barchart depicts each participant's wear-time (red), sleep diary (green) and symptoms submission (blue).

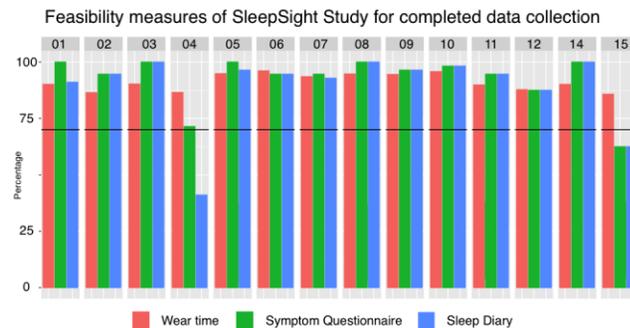
series. In our case we wanted to prioritise quantification of our participant's behavior and detect early signs of relapse.

In order to achieve the latter, we trained a generalising Gaussian Process (GP) with a periodic (sinusoid) kernel on days on which a participant scored particularly low symptom scores. Deviations from this model could then be quantified and evaluated (Figure 3).

Results

The study included 16 participants of which 14 completed the study successfully based on our acceptability criteria of at least 70% wear-time and questionnaire submission over a period of 8 weeks (days n=56). Figure 4 shows user acceptance in more detail.

Our GP anomaly detection methodology is still a work in progress and hence we are unable to present valuable results regarding behavior quantification at this point.



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