Capitalizing on wearable sensors and smartphones to robustly assess longitudinal symptom severity trajectories

Application in mental disorders, post-traumatic stress disorder, and stroke

Dr Athanasios Tsanas (‘Thanasis’)  atsanas@ed.ac.uk
Associate Professor in Data Science
Usher Institute, Medical School
University of Edinburgh
Research vision

Address unmet clinical needs

Assessment & Monitoring

- Frequent
- Unobtrusive
- Personalised
- Inexpensive
- Massive scale
Mental health telemonitoring (AMoSS project)

Project 1
Problem with current assessment

Physical presence in the clinic
- Cumbersome for those living in remote areas
- People need to take days off work

Patient-led self-monitoring
- Recall bias
- Subjectivity

No ground truth
- Difficult to objectively assess intervention effects
- Inter-rater variability
Proposed solution

- Frequent **time-stamped** self-reports
- Sensor-based **objective** monitoring
Assessing mental health

- Continuous personalized monitoring
- Objectively quantify mental health
- Identify characteristic patterns
AMoSS project data

- 48 Bipolar Disorder (BD)
- 31 Borderline Personality Disorder (BPD)
- 51 Healthy Controls (HC)

- Questionnaires: ASRM, QIDS, GAD-7 + MZ (novel)
- Data collected over a year for most participants
Self-assessment: questionnaires

Quick Inventory of Depressive Symptomatology—Self-Report (QIDS-SR)

Please circle the one response to each item that best describes you for the past seven days.

1. Falling asleep:
   0 I never take longer than 30 minutes to fall asleep.
   1 I take at least 30 minutes to fall asleep, less than half the time.
   2 I take at least 30 minutes to fall asleep, more than half the time.
   3 I take more than 60 minutes to fall asleep, more than half the time.

2. Sleep during the night:
   0 I do not wake up at night.
   1 I have a restless, light sleep with a few brief awakenings each night.
   2 I wake up at least once a night, but I go back to sleep easily.
   3 I awaken more than once a night and stay awake for 20 minutes or more, more than half the time.

3. Waking up too early:
   0 Most of the time, I awaken no more than 30 minutes before I need to get up.
   1 More than half the time, I awaken more than 30 minutes before I need to get up.
   2 I almost always awaken at least one hour or so before I need to, but I go back to sleep eventually.
   3 I awaken at least one hour before I need to, and can’t go back to sleep.

4. Sleeping too much:
   0 I sleep no longer than 7–8 hours/night, without napping during the day.
   1 I sleep no longer than 10 hours in a 24-hour period including naps.
   2 I sleep no longer than 12 hours in a 24-hour period including naps.
   3 I sleep longer than 12 hours in a 24-hour period including naps.

5. Feeling sad:
   0 I do not feel sad.
   1 I feel sad less than half the time.
   2 I feel sad more than half the time.
   3 I feel sad nearly all of the time.

6. Decreased appetite:
   0 There is no change in my usual appetite.
   1 I eat somewhat less often or lesser amounts of food than usual.
   2 I eat much less than usual and only with personal effort.
   3 I rarely eat within a 24-hour period, and only with extreme personal effort or when others persuade me to eat.
AMoSS adherence >80%

- Longitudinal, daily monitoring of mood

## Interpretable clinical latent variables

<table>
<thead>
<tr>
<th></th>
<th>P1</th>
<th>P2</th>
<th>P3</th>
<th>P4</th>
<th>P5</th>
<th>P6</th>
</tr>
</thead>
<tbody>
<tr>
<td>Anxious</td>
<td>0.55</td>
<td>0.08</td>
<td>-0.47</td>
<td>-0.27</td>
<td>0.60</td>
<td>0.18</td>
</tr>
<tr>
<td>Elated</td>
<td>-0.11</td>
<td>0.76</td>
<td>-0.11</td>
<td>-0.53</td>
<td>-0.33</td>
<td>0.01</td>
</tr>
<tr>
<td>Sad</td>
<td>0.52</td>
<td>0.04</td>
<td>-0.43</td>
<td>0.39</td>
<td>-0.57</td>
<td>-0.25</td>
</tr>
<tr>
<td>Angry</td>
<td>0.42</td>
<td>0.11</td>
<td>0.46</td>
<td>0.11</td>
<td>-0.21</td>
<td>0.74</td>
</tr>
<tr>
<td>Irritable</td>
<td>0.47</td>
<td>0.12</td>
<td>0.60</td>
<td>-0.15</td>
<td>0.14</td>
<td>-0.60</td>
</tr>
<tr>
<td>Energetic</td>
<td>-0.13</td>
<td>0.62</td>
<td>0.020</td>
<td>0.67</td>
<td>0.38</td>
<td>-0.03</td>
</tr>
</tbody>
</table>

| % Total variance explained | 55  | 77  | 85  | 91  | 97  | 100 |

| Tentative interpretation | “Negative feelings” | “Positive feelings” | “Irritability” |

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Self-assessment: questionnaires

Missing data (example)

Potentially conveys information

Identify patterns of missing data and scores
Geolocation and depression

Circadian variability and mood in mental disorders

- AMoSS-Proteus dataset
  - “High intensity” monitoring
  - Mapping circadian variability to mood

Smartwatch processing

Raw data
Processed patterns
Features

Extract data
Pre-process
Characterise

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Visualize multimodal data

- Database with all participants
  (used to blank out participant id)
Summary of data modalities

(HC), 04 Jan 2021 - 02 Feb 2021

Sleep (estimate)
Non-wear (estimate)
Actogram

(HC), 05 Jan 2021 - 02 Feb 2021

Time over two consecutive days
Colored actogram

(HC), 05 Jan 2021 - 02 Feb 2021

Activity level

High

Low

Non-wear

Time in day

00:00  04:00  08:00  12:00  16:00  20:00  24:00

Tue, 5 Jan
Wed, 6 Jan
Thu, 7 Jan
Fri, 8 Jan
Sat, 9 Jan
Sun, 10 Jan
Mon, 11 Jan
Tue, 12 Jan
Wed, 13 Jan
Thu, 14 Jan
Fri, 15 Jan
Sat, 16 Jan
Sun, 17 Jan
Mon, 18 Jan
Tue, 19 Jan
Wed, 20 Jan
Thu, 21 Jan
Fri, 22 Jan
Sat, 23 Jan
Sun, 24 Jan
Mon, 25 Jan
Tue, 26 Jan
Wed, 27 Jan
Thu, 28 Jan
Fri, 29 Jan
Sat, 30 Jan
Sun, 31 Jan
Mon, 1 Feb
Objective signal monitoring

Actogram: 14004 (HC), 01-Feb-2014 - 14-Feb-2014

<table>
<thead>
<tr>
<th>Feature</th>
<th>Subject id</th>
</tr>
</thead>
<tbody>
<tr>
<td>IS</td>
<td>0.66 ± 0.07</td>
</tr>
<tr>
<td>IV</td>
<td>0.01 ± 0.00</td>
</tr>
<tr>
<td>L5</td>
<td>0.00 ± 0.00</td>
</tr>
<tr>
<td>M10</td>
<td>0.16 ± 0.01</td>
</tr>
<tr>
<td>RA</td>
<td>0.95 ± 0.02</td>
</tr>
</tbody>
</table>

(results in form: median±iqr)

IS = interdaily stability
IV = intradaily variability
RA = relative amplitude = (M10-L5)/(M10+L5)

High IS: good zeitgeber sync 😊
High IV: fragmentation 😞
High RA: good rhythmicity 😊

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### Actograms + Questionnaires

**Actogram: 14047 (BD), 04-Jul-2014 - 10-Jul-2014**

- **Fri, 4 Jul**: [Graph showing activity patterns]  
- **Sat, 5 Jul**: [Graph showing activity patterns]  
- **Sun, 6 Jul**: [Graph showing activity patterns]  
- **Mon, 7 Jul**: [Graph showing activity patterns]  
- **Tue, 8 Jul**: [Graph showing activity patterns]  
- **Wed, 9 Jul**: [Graph showing activity patterns]

<table>
<thead>
<tr>
<th>Feature</th>
<th>Median ± IQR</th>
</tr>
</thead>
<tbody>
<tr>
<td>IS</td>
<td>0.65 ± 0.09</td>
</tr>
<tr>
<td>IV</td>
<td>0.01 ± 0.00</td>
</tr>
<tr>
<td>L5</td>
<td>0.00 ± 0.00</td>
</tr>
<tr>
<td>M10</td>
<td>0.17 ± 0.00</td>
</tr>
<tr>
<td>RA</td>
<td>0.95 ± 0.04</td>
</tr>
</tbody>
</table>

**Actogram: 14047 (BD), 04-Oct-2014 - 12-Oct-2014**

- **Sat, 4 Oct**: [Graph showing activity patterns]  
- **Sun, 5 Oct**: [Graph showing activity patterns]  
- **Mon, 6 Oct**: [Graph showing activity patterns]  
- **Tue, 7 Oct**: [Graph showing activity patterns]  
- **Wed, 8 Oct**: [Graph showing activity patterns]  
- **Thu, 9 Oct**: [Graph showing activity patterns]  
- **Fri, 10 Oct**: [Graph showing activity patterns]  
- **Sat, 11 Oct**: [Graph showing activity patterns]

<table>
<thead>
<tr>
<th>Feature</th>
<th>Median ± IQR</th>
</tr>
</thead>
<tbody>
<tr>
<td>IS</td>
<td>0.72 ± 0.08</td>
</tr>
<tr>
<td>IV</td>
<td>0.01 ± 0.00</td>
</tr>
<tr>
<td>L5</td>
<td>0.00 ± 0.00</td>
</tr>
<tr>
<td>M10</td>
<td>0.17 ± 0.02</td>
</tr>
<tr>
<td>RA</td>
<td>0.97 ± 0.03</td>
</tr>
</tbody>
</table>

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Looking at colleagues’ work...

- Psyche system (t-shirt based)


- Lifelogging (cameras)
PTSD objective treatment assessment using a smartwatch

Project 2
Problem with current assessment

Physical presence in the clinic
- Cumbersome for those living in remote areas
- People need to take days off work

Patient-led self-monitoring
- Recall bias
- Subjectivity

No ground truth
- Difficult to objectively assess intervention effects
- Inter-rater variability
PTSD project data

- 42 PTSD participants
- 43 traumatized controls
- 51 Healthy Controls (HC)

- Smartwatch (~1month)
- Sleep diaries + PSQI
- Collected before + after treatment
Sleep detection example

![Diagram showing sleep detection results for a trauma participant over a period of time. The diagram includes graphs for movement, light, temperature, and XYZ coordinates. The graphs are color-coded to represent different states such as non-wear, asleep, and sleep diary. The date range is from November 22 to November 28, 2015.]

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## Sleep detection comparisons

<table>
<thead>
<tr>
<th>Deviation from grand truth (minutes)</th>
<th>van Hees et al. (2015) sleep detection algorithm</th>
<th>Proposed sleep detection algorithm in this study</th>
</tr>
</thead>
<tbody>
<tr>
<td>Non-traumatised controls</td>
<td>Sleep onset: -56±112, Sleep offset: 22.5±106</td>
<td>Sleep onset: -12.5±51, Sleep offset: 2±30.25</td>
</tr>
<tr>
<td>Traumatised controls</td>
<td>Sleep onset: -81±147, Sleep offset: 35.5±95.5</td>
<td>Sleep onset: -18±50, Sleep offset: 10±46.75</td>
</tr>
<tr>
<td>PTSD participants</td>
<td>Sleep onset: -78±131.25, Sleep offset: 41.5±122.5</td>
<td>Sleep onset: -34±78.25, Sleep offset: 10±45.25</td>
</tr>
</tbody>
</table>

PTSD, before and after treatment
Stroke objective assessment using a smartwatch
Stroke project data

- 27 participants
- No normative data (no HC)

- Smartwatch (~1 month)
- Questionnaires (anxiety, fear)
- Collected before + after different treatment
Current and future work

Wearables
- New algorithms
- New insights

App-based monitoring
- PROMs
- Passive data

The “invisibles”
- Electromagnetic monitoring
Conclusions

- Easy to collect data often convey clinically useful information
- Moving towards **passively collected data**
- Fertile field to be developing algorithmic tools
- Need for interdisciplinary collaboration to make breakthroughs
Data and code available:

- Data from different projects
- Toolboxes (Matlab code)
  - Time-series analysis
  - Actigraphy
  - ML methods
Collaborators

Stanford
Colorado
LSVT
MIT
GTech
Miami
NIN
UPM
UoA
IIT Delhi
IIT Kharagpur
UTFSM
York
Liverpool
Aston
Cardiff
Oxford
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