Developing a digital platform for remote healthcare monitoring

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What is a platform?

From Oxford dictionary:

“a raised level surface, for example one that equipment stands on or is operated from.”

“the type of computer system or the software that is used.”
Remote monitoring for Dementia care

Globally ~50m People

By 2050 ~130m People

In the UK, 1 in 4 Hospitals beds
Mission: To transform dementia care through the use of new technology

Care is limited by lack of real world data

Opportunities from the integration of new technologies for home monitoring with machine learning/AI

Holistic approach to major real-world problems

- Personalised intervention
- Sleep disturbance
- Infections
- Agitation/aggression
- Social isolation

85% would prefer to live at home for as long as possible

1 in 4 hospital beds for people living with dementia

70% increase over the last 5 years
People with dementia typically spend £100,000 on the care they need – many spend much more

People affected by dementia shoulder two thirds of all dementia care costs in the UK

Dementia care can be up to 40% more expensive than standard social care

~22% of unplanned hospital admissions in people with dementia are due to preventable causes

Source: Alzheimer’s Society
Access to care

Patients whose care has been reviewed in the preceding 12 months

As dementia is a long-term and degenerative condition, the needs of the individual and carers will change with time and circumstances. Reviewing those with a diagnosis at least annually will ensure that the needs of people with dementia and their carers are discussed and appropriate care plans can be implemented.

This metric shows the number of patients with a diagnosis of dementia who have had their care reviewed (face-to-face) in the preceding 12 months as a proportion of all patients on the disease register with dementia (including exceptions):

- Larger is better

Data: DEM002: Dementia care has been reviewed last 12 months (cien.incl.exc.) Quality Outcomes Framework (QOF), NHS Digital: 2014/15
Details: digital.nhs.uk/catalogue/PUB18887

NHS Somerset CCG: 48.32%
2,608 of 5,338 people
Dementia care

85% would prefer to live at home for as long as possible
In-home monitoring sensors

Physiological

- Heart
- Blood pressure
- Weight

Environmental

- Room temperature
- Humidity
- Bedding
- Water boiling
But it didn’t start from here…

Let’s go back a few years…

Technology Integrated Health Management (TIHM)

Who is involved?

The project is led by Surrey & Borders NHS Foundation Trust working with the University of Surrey, Royal Holloway University of London, Kent, Surrey and Sussex Academic Health Science Network, the Alzheimer’s Society, local Clinical Commissioning Groups, charities and ten technology companies.

The project will also have a user advisory forum made up of people who use health and social care services and their carers. It will also have an expert advisory forum, including representatives from industry, the voluntary sector and a Clinical Commissioning Group.
Technology Integrated Healthcare Management (TIHM)

Design ver. 0.1

Data Analytics Engine
- Privacy
- Health and Safety
- Monitoring and Alert
- Security
- Reliability

IoT Test Bed Cloud
- Possible links to Other Test Beds

External NHS, GP IT systems

HyperCat

Gateway

Data-driven and patient centered Healthcare Applications

Healthcare professionals

Family and caregivers

Alzheimer’s Society

Gateway

Peer "Future is Here"

Gateway
Digital platform - Integrated view
Integrated view - Clinical view
Transforming care pathways

(Enshaeifar, Skillman et al, WebConf2020)
Activity data

<table>
<thead>
<tr>
<th>Week Number</th>
<th>bathroom</th>
<th>bedroom</th>
<th>hallway</th>
<th>kettle</th>
<th>Activity Location</th>
<th>kitchen</th>
<th>lounge</th>
<th>microwave</th>
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<tr>
<td>201901</td>
<td>56</td>
<td>63</td>
<td>53</td>
<td>18</td>
<td>27</td>
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<td>6</td>
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<tr>
<td>201902</td>
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<td>63</td>
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<td>18</td>
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<td>201903</td>
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<tr>
<td>201904</td>
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<td>63</td>
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<td>18</td>
<td>27</td>
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<td>201905</td>
<td>58</td>
<td>63</td>
<td>53</td>
<td>18</td>
<td>27</td>
<td>219</td>
<td>6</td>
<td></td>
</tr>
</tbody>
</table>

... (more data)
Daily activity pattern analysis

Aggregated daily activities

- Bedroom
- Kitchen
- Bathroom
- Kettle
- Toaster
- Front door
Machine learning for daily pattern analysis

(Enshaeifar et. al, 2018)
Timeline of events for one patient

- **05/09-14/09**: Patient is septic, hospitalised for UTI
- **13/11-02/12**: Patient is hospitalised
- **04/12-14/12**: Patient is hospitalised
- **14/01**: Routine urine test (+ve)
  - GP called
- **12/02**: Routine urine test (+ve)
  - Changes in microbiome
- **14/03**: Routine urine test (+ve)
  - Changes in microbiome

**2019**
- **09/10**: Flag: Agitation (-ve)

**2020**
- **04/12**: Spike in AM movement activity
- **05-18/01**: Flag: UTI
  - Revised algorithm generates 11 alerts in 20 days
- **24/01**: GP Confirms UTI
  - Patient treated
- **13/02**: Flag: Agitation (+ve)
  - PwD agitated if carer leaves for extended period
Early indicators

Common alert triggers July - Nov 2017 following analysis of 11,198 alerts

UTI's are a top five cause of hospital admission among this group
Data challenges - I

- Noisy and incompleteness
- Quality and validation
- Variability in data due to:
  - Changes in health condition
  - Visitors and pets in the home
  - Seasonal and daily pattern changes
- Missing values (connectivity, technical issues and user compliance)
Analytical models

- Behavioural analysis
  - Agitation, changes in daily activity

- Healthcare conditions
  - Urinary Tract Infections (UTIs)
  - Risk analysis for adverse health conditions

- Can we use the data and existing clinical knowledge to train models to analyse the risks for different conditions?
Urinary Tract Infection (UTI) risk analysis
All good, but…

- Generalisability is a key problem!

- How to improve the performance of the algorithms for large-scale and diverse data? Unknown and unseen patterns? rare events?
Data challenges - II

- Noisy and incomplete
- Quality and verification
- Variability in data due to:
  - Changes in health condition
  - Visitors and pets in the home
  - Seasonal and daily pattern changes
- Missing values (connectivity, technical issues and user compliance)
- Training samples and labelling
- Imbalance in the training data (TP, FP, TN, FN)
- Granularity of the data (especially for the basic physiology)
Urinary Track Infection (UTI) risk analysis

(a) Daily activity patterns for a PLWD on a day without UTI (left) and another day with a positively diagnosed UTI (right).

(b) The risk of UTIs calculated by our semi-supervised model for each PLWD in the UK DRI CR&T study in February and early March 2021.
Semin-supervised learning
UTI risk analysis: learning model

101
Date: 2020-01-23

Raw Data → Neural Networks → Extracted Features → Probabilistic Neural Network → Likelihood → Decision

101
Date: 2019-09-03

Raw Data → Neural Networks → Extracted Features → Probabilistic Neural Network → Likelihood → Decision

* Physiological data × sample distribution y: kernel distribution
Remote monitoring

Home Monitoring

- Behaviour
- Medication
- Sleep
- Infection
- Robotics

Encrypted home storage

Cloud Computing

AI/ Machine Learning

Data integration & Intelligent decision-making

Proactive Personalised Intervention

Limited, secure

Private

Movement sensor
Door sensor
BP cuff
Smart plugs
Smart watch
Urine testing
Weighing/Hydration scales

Minder

UK Dementia Research Institute
Living lab
# In-home observation and measurement data

<table>
<thead>
<tr>
<th>Metrics</th>
<th>Granularity</th>
</tr>
</thead>
<tbody>
<tr>
<td>Environmental</td>
<td>Light, Room temperature</td>
</tr>
<tr>
<td>Cardio</td>
<td>HR BPM</td>
</tr>
<tr>
<td>Activity</td>
<td>Motion, Doors, Appliances</td>
</tr>
<tr>
<td>Scales</td>
<td>NPI, MMSE, etc.</td>
</tr>
<tr>
<td>Sleep</td>
<td>Sleep Mat</td>
</tr>
<tr>
<td>Physiology</td>
<td>Body temperature, weight etc.</td>
</tr>
<tr>
<td>Well-being</td>
<td>Daily questions</td>
</tr>
</tbody>
</table>

The UK DRI CR&T Cohort since September 2019.

Past (TIHM) + Present (UK DRI) data:
- >40,000 days of activity data from 170 homes
- >20,000 nights of sleep data
Longitudinal data
Minder platform
Communication
- Notification (face-to-face)
  - 5 days ago

Procedure
- SARS-CoV2 test of previous infection – lateral flow antibody test
  - 5 days ago
- SARS-CoV2 test of acute infection – lateral flow blood antigen test
  - 5 days ago

Encounter
- Telephone Help Line

Devices
<table>
<thead>
<tr>
<th>Device</th>
<th>Location</th>
<th>Latest Observation</th>
<th>Status</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gateway device</td>
<td>Home</td>
<td></td>
<td>unknown</td>
</tr>
<tr>
<td>Electronic sphygmomanometer</td>
<td>Home</td>
<td>4 hours ago</td>
<td>active</td>
</tr>
<tr>
<td>Forehead thermometer</td>
<td>Home</td>
<td>2 days ago</td>
<td>active</td>
</tr>
<tr>
<td>Pulse oximeter</td>
<td>Home</td>
<td>14 hours ago</td>
<td>active</td>
</tr>
<tr>
<td>Patient-monitoring bed mattress cover</td>
<td>Home</td>
<td></td>
<td>active</td>
</tr>
<tr>
<td>Scale</td>
<td>Home</td>
<td>5 hours ago</td>
<td>active</td>
</tr>
<tr>
<td>Passive infrared sensor</td>
<td>Hallway</td>
<td>an hour ago</td>
<td>active</td>
</tr>
<tr>
<td>Passive infrared sensor</td>
<td>Kitchen</td>
<td>28 minutes ago</td>
<td>active</td>
</tr>
<tr>
<td>Passive infrared sensor</td>
<td>Bedroom</td>
<td>an hour ago</td>
<td>active</td>
</tr>
<tr>
<td>Passive infrared sensor</td>
<td>Living room</td>
<td>21 minutes ago</td>
<td>active</td>
</tr>
</tbody>
</table>
Graphs created by Eyal Soreq, UK DRI Care Research and Technology Centre, Cognitive and Behaviour programme, Imperial College London.
Hidden technical debt in real-world ML systems

Only a small fraction of real-world ML systems is composed of the ML code.

Vision for the research going forward

- Creating a scalable platform that be applied across a range of dementia studies and other relevant conditions and supporting personalised care.

- Constructing clinically-driven AI and machine learning models that automatically adapt to dynamic changes in incoming data and continually learn without compromising the quality of predictions.

- Providing safe and robust in-home and federated storage and processing methods while users are in control of their data.
The DRI Care Research and Technology Centre

- Voice control & Conversation
- Sleep, Environmental control
- Synthetic biology
- Social Robotics
- Biosensor hardware and Monitoring technologies
Our participant’s perspective

Afzal

I feel reassured that there’s a way ahead and it’s not a dark future

Zohra

We don’t think of it as a smart home

I would hate to go into care, this is the next best thing

It takes the scary bits away; it means I’m not on my own

It is invisible support for carers

https://tinyurl.com/dementianewhorizon
With thanks to our trusted users and participants in the study
The programme team

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Thank you

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