Enabling Trust, Accountability, and Routine Use of AI-Enabled Healthcare

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We are living longer! But, this means more chronic illness.

**Diabetes**
422 million worldwide
Almost 4x more than 1980

(Mathers 2006)

**Heart failure**
6.5 million in USA
Predicted to rise 46% by 2030

(American Heart Association 2017)

Doctors are facing *increasing workload* and a need for more *personalised care*. 

*Challenges facing healthcare*
Typical clinical scenarios

Example scenario:

- Patient presents to a doctor with heart palpitations (irregular heart rate)
- She has had palpitations for the past few weeks
- Doctor examines the patient and asks about their medications and lifestyle
- Doctor then refers patient for an EKG
- Three weeks latest, EKG doesn’t reveal anything.
- Doctor concludes the palpitations were caused by atrial fibrillation.
Where could AI help medicine?

AI could help doctors get a better understanding of patients.

For our patient, AI could help the doctor identify the cause of the patient’s palpitations.

But where can we get the data?
Patient-Generated Data

Any kind of data which a patient has recorded using their own means.

- **Wearables**
  - Fitbit, Apple Watch

- **Smartphone apps**
  - Google Fit, Strava

- **Health products**
  - Blood pressure cuffs, weighing scales

- **Journals**
  - Hand-written and electronic
Health Self-Tracking Tools are Increasingly Popular

One third of US adults track at least one indicator of health (such as weight or symptoms) on using an app (MobiHealth News 2013)

Over 15 million Fitbits sold in first quarter 2017 (Statista 2018)
Food tracking

Apps like DietLens help people track their calorie intake by analysing photos of food.

We asked 13 clinicians about the future of healthcare

<table>
<thead>
<tr>
<th>Clinical role</th>
<th>Participants</th>
<th>Years in practice</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cardiologist</td>
<td>P1, P2, P3, P4</td>
<td>All 20+ years</td>
</tr>
<tr>
<td>Mental health specialist</td>
<td>P5, P6</td>
<td>10 years, 5 years</td>
</tr>
<tr>
<td>Emergency doctor</td>
<td>P7</td>
<td>5 years</td>
</tr>
<tr>
<td>Junior surgeon</td>
<td>P8</td>
<td>5 years</td>
</tr>
<tr>
<td>Hospital doctor</td>
<td>P9</td>
<td>4 years</td>
</tr>
<tr>
<td>General practitioner</td>
<td>P10</td>
<td>20+ years</td>
</tr>
<tr>
<td>Heart failure nurse</td>
<td>P11</td>
<td>20+ years</td>
</tr>
<tr>
<td>Oncology nurse</td>
<td>P12</td>
<td>2 years</td>
</tr>
<tr>
<td>Audiologist</td>
<td>P13</td>
<td>3 years</td>
</tr>
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All were practicing in the UK
What do doctors think the future of healthcare look like?

1. Fill the gaps between visits
2. Contextualise clinical data
3. Greater patient participation
In the hospital of the 2050?

Demo: http://flamingtempura.github.io/pgd-view
In the hospital of the 2050?

Monday 10am: palpitations
● 2 hours sleep

Tuesday 12pm: palpitations
● 4 hours sleep

Thursday 2pm: palpitations
● 3 hours sleep

Poor sleep was leading to worse palpitations.
But how will doctors perceive AI?

Some doctors have resisted the idea of using AI in healthcare.

Will patient privacy be upheld?

Will patients trust it?
Understanding the privacy concerns of mobile health apps users

Reham Al Tamime
Research Problem

- The privacy decisions become more complex.
- Lack of understanding of users’ privacy concerns about the data collection and sharing practices in different contexts.
- Users are still provided with traditional privacy management options.
Research Goals

- To understand the privacy concerns of mobile health app users:
  a. To understand the comfort level in sharing data across various contexts.
  b. To investigate how crowdsourcing can help to understand privacy preferences.
Theory of contextual integrity

- Contextual integrity ties adequate protection for privacy to norms of specific contexts [Helen Nissenbaum, 2004].

- Information gathering and dissemination be appropriate to that context and obey the governing norms of distribution within it.

- Capturing and specifying context elements of data collection and sharing are of great importance.
### Scenarios of contexts

<table>
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<tr>
<th>Type of data</th>
<th>Location</th>
<th>Whether the data is shared with a third party</th>
<th>Purpose of data sharing</th>
<th>Retention</th>
</tr>
</thead>
</table>

1. **Type of data**
2. **Location**
3. **Whether the data is shared with a third party**
4. **Purpose of data sharing**
5. **Retention**
Zooniverse

- Crowdsourcing, by definition, is the use of humans (at scale) to complete computationally difficult or time consuming tasks.

- Crowdsourcing for citizen science has been used to help annotate scientific datasets, such as Hubble Telescope images.

- 432 scenarios in total -> 16 subsets -> 27 scenario each.
Scenario 20

How comfortable are you with the data collection and sharing in the following scenario?

Your healthcare mobile app is keeping records of eating and diet patterns. Information about eating and diet patterns is shared with a third party to advertise for products and services. This data will be kept by the third party for an unspecified period of time.

Choose your level of comfort:
- Comfortable
- Very comfortable
- Uncomfortable
- Very uncomfortable
- Neither comfortable nor uncomfortable

Options:
- Cancel
- Identify

Next →
Trust in AI healthcare technology

- Build framework that provides crowd-based privacy support for sharing data in various contexts.
- Design AI technologies that take into consideration users’ privacy concerns.
Personalized Medicine

One-Size-Fits-All works only partially

Fail to respond to treatment

- 38% depression
- 40% asthma
- 75% cancer

Use of massive datasets and machine learning to design treatments for individuals
algorithms + data structures = programs

- Niklaus Wirth (1976)
  - Algorithms and data structures are intimately related
  - If you want to sort, use arrays

- Opacity of algorithms
  - Trade secrets
  - Technical literacy
  - Characteristics of the algorithm and the scale required to apply them usefully
  - National Nurses Union
    - “Algorithms are simple mathematical formulas that nobody understands”
Algorithmic programming: (PL/I)
The Invisible Maniac was algorithmic
Machine learning

- Machines trained from data
  - Classifiers produce categories
  - Learners train on data (based on models) and produce weights
  - Inductive reasoning

- “Applications that cannot be programmed by hand”
Black Box Medicine

- Opaque computational models to make decisions or judgements related to healthcare
- Use of large scale datasets and associated algorithms (and heuristics) to use implicit, complex connections between multiple patient characteristics
- Algorithms are neither explicit nor transparent
- Relationships they capture cannot be explicitly understood
- Relationships often cannot be explicitly stated
- This is not deliberately hidden—it is a consequence of complexity
Challenges for the Patient

- How to explain treatment plan to a patient
  - Patients often do not understand information or retain it
- Subgroups have different levels of trust in healthcare
  - White women | African American women
  - Native born | Immigrants
- Predictive categorization not based on who/what you are
  - A viewer likely to enjoy a movie (Netflix)
  - A customer likely to buy this item (amazon)
  - A teenager likely to commit a crime (NYC predictive policing)
  - A women likely to become pregnant
  - A genotype likely to respond to CBT to treat schizophrenia
Challenges for the Doctor

- Treatments and care pathways rely on complex biological interactions through integration of information from interdisciplinary fields holistically
  - Common in Systems Biology
  - Not part of mainstream clinical research
    - How do we develop/train doctors?
- Quality of machine learning relies on aspects of training data and models
  - Who is responsible?
- Deductive reasoning in medicine
  - Test a theory empirically—randomized clinical trials
- Inductive reasoning (Black Box Medicine)
  - Pattern recognition
  - Inductive reasoning not trusted among medics since it yields false positives
Challenges

- Policy
  - Equity across populations
- Institutions
  - Governance structures
- Technical
  - Systems to produce an audit trail
    ■ (This is not trivial...)
Conclusion: Enabling Trust, Accountability, and Routine Use of AI-Enabled Healthcare

Policy and societal challenges relating to privacy, trust, and transparency

(We can’t just throw programmers at the problem)

Our challenge to the NExT++ Workshop:

How can we build the next generation of accountable AI?
Our Published Research

Web Science Conference, Amsterdam, Netherlands

CHI 2018, Montreal, Canada

Frontiers Public Health.

CHI 2016, San Jose, USA. (Honorable Mention)

See our posters outside!