Opportunities and Challenges of Learning Health Systems

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About the presenter

University of Manchester

Field: Health Informatics
Background: Computer Science / AI
Research interests:
- prediction models
- clinical decision support systems
- electronic health records

Utrecht

University of Amsterdam

Niels

University of Manchester, UK
External flagship for the University of Manchester's health technology portfolio

Integrates research from all faculties to accelerate the translation of health technologies, and create opportunities for business growth – including economic, social and behavioural aspects

Improve the connection between technology development, innovation, health research, and real-world impact

Focus areas:
• digital technologies
• artificial intelligence
• advanced materials
This talk

1. What are learning health systems?
2. Why do we need them?
3. Discussion: What are the challenges?
4. Example: SMASH and the GM Care Record
5. Conclusions
What is a Learning Health System?

A system in which science, informatics, incentives, and culture are aligned for continuous improvement, innovation, and equity:

- best practices and discovery seamlessly embedded in the delivery process
- individuals and families are active participants in all elements
- new knowledge is generated as an integral by-product of healthcare delivery

[Institute of Medicine, 2006]
Breaking down barriers

real world → learning → improvement → research
The landscape is changing ...

Traditional research data
• trials
• case-control studies
• cohort studies

Omics data
• genome
• proteome

Routine care data
• audits / registries
• administrative data
• electronic health records

Wearable sensors

Smartphones
• symptoms
• GPS

Home based sensors
• weighing scales
• blood pressure monitors
• glucose meters
Learning from every patient

Learning health systems harnesses the power of data and analytics to learn from every patient, and feed the knowledge of “what works best” back to clinicians, public health professionals, patients, and other stakeholders to create cycles of continuous improvement.
Credit card companies routinely collect data on all credit card transactions.

They use data mining methods to create a “safety net” that issues early warnings when fraud is suspected.

The safety net:
- learns from every transaction
- is continuously updated
- varies by region/country
- is fully integrated with services
The learning health cycle

1. Collect Data
2. Assemble Data
3. Analyze Data
4. Interpret Results
5. Represent Knowledge
6. Manage Knowledge
7. Apply Knowledge
8. Take Action to Change Practice

A Problem of Interest

Data to Knowledge Flow

Knowledge to Practice Flow

Practice to Data Flow

FLYNN ET AL.

The University of Manchester

Flynn et al., Learn Health Sys. 2018;2:e10054.
The LHS infrastructure
LHSs can exist at any level of scale

- Single Organization
- Network of organisations
- Nation
- Planet

ManchesteR 1824
The University of Manchester
What the LHS is not

- A technology
- An intervention
- "AI"
- Finished

*Leci n’est pas une pipe.*
Characteristics of a fully functional Learning Health System

1. Secure availability of relevant data to learn from

2. Decision support, based on knowledge derived from these data

3. Learning and health improvement are routine and continuous processes

4. Infrastructure enables the routine execution of multiple learning cycles

5. Stakeholders within the system view these activities as part of their culture
Why do we need learning health systems?
Number of trials grows exponentially
Clinical trial costs

Figure 3: Clinical Trial Costs (in $ Millions) by Phase and Therapeutic Area

Source: US Department of Health and Human Services, 2014
About 25% of the population have more than 1 long-term condition

About 25% of the population have more than 1 long-term condition.

78% of primary care consultations

Most patients with multimorbidity are excluded from trials

He et al. Trials 2020; 21:228
Learning from Big Health Care Data
Sebastian Schneeweiss, M.D., Sc.D.

The routine operation of modern health care systems produces an abundance of electronically stored data on an ongoing basis. It’s widely acknowledged that there is great potential for utilizing these data, within the system that generates them, to inform treatment choices in ways that improve patient care and health outcomes. Imagine entering your office in the morning and finding an e-mail message reading, “Thanks to your new vaccination screening program, as of yesterday your practice had given 120 more vaccinations than similar practices had.” Or “As compared with the period before your network’s implementation of the new policy of referring patients with atrial fibrillation to the anticoagulation center, seven strokes have been averted, but two additional upper GI bleeds have occurred.” Or even “Judging from her track record and the characteristics noted in her medical record, there is an 80% likelihood that Patient C, whom you are about to see, will not fill her prescription for an antihypertensive.” In theory, such ongoing structured learning based on routinely collected data could seamlessly augment the knowledge physicians have gleaned from their experience, which involves the same patients and more detailed observations but is less formal in its evaluation processes and more likely to be subject to unintended bias.

Two key “learning” applications of big health care data that hold the promise of improving patient care are the generation of new knowledge about the effectiveness of treatments and the prediction of outcomes. Both these functions exceed the bounds of most computer applications currently used in health care, which tend to offer physicians such tools as context-sensitive warning messages, reminders, suggestions for economical prescribing, and results of mandated quality-improvement activities. Physicians currently struggle to apply new medical knowledge to their own patients, since most evidence regarding the effectiveness of medical innovations has been generated by studies involving patients who differ from their own and who were treated in highly controlled research environments. But many data that are routinely collected in a health care system can be used to evaluate medical products and interventions and directly influence patient care in the very systems that generated the data.
Benefits of Electronic Health Records

- Representative of real-world populations
- Very large cohorts sizes (e.g. CPRD Aurum: 17m)
- Longitudinal data
- Very long follow-up times (UK primary care >20 years)
- Available against low cost
Discussion: What are the challenges in creating learning health systems?
How long will it take to create learning health systems?

- 1 year
- 5 years
- 10 years
- It will never happen
- It should never happen

sli.do
#402911
What are the challenges in creating learning health systems?

- The LHS infrastructure is capable of engendering virtuous cycles of health improvement
- The LHS is trusted and valued by all stakeholders
- The LHS is economically sustainable and governable
- The LHS is adaptable, self-improving, stable, certifiable, and responsive

Friedman et al. J Am Med Inform Assoc 2014;0:1–6.
Electronic Health Records: Limitations

• The data were not collected for research
  – incomplete data
  – variable follow-up times
  – selection biases (e.g. lack of attendance)
  – variable data quality (e.g. depth of coding)

• Retrospective cohort / case-control design
  – no protocol for either clinical management or data collection

• Confounding
  – routine care
  – hard to make causal inferences
Electronic Health Records: Challenges

**Fragmented data**
- data often collected in "silos" with poor inter-operability

**Data protection**
- we need to protect people's privacy to ensure their trust in the LHS
- data protection rules are becoming increasingly complex

**Phenotyping**
- we need to reconstruct clinically meaningful concepts from transactional data
Innovative IT system that prevents prescription errors wins prestigious national prize

Richard Williams, a Senior Software Engineer at The University of Manchester, based in the NIHR Greater Manchester Patient Safety Translational Centre (Greater Manchester PSTRC) and Centre for Health Informatics, has been awarded the respected John Perry Prize by BCS: The Chartered Institute for IT.

Announced at a glitzy ceremony in early October, the prize recognises Richard’s outstanding contribution to Primary Care Computing. Having been awarded annually since 1985 it is one of the IT industry’s most respected accolades, acknowledging innovation and excellence in computer science.

The Prize along with £500 cash was awarded in recognition of Richard’s work developing and disseminating the Smart Medication Safety Dashboard (SMASH). This potentially life-saving piece of software, which was developed with support from the Greater Manchester PSTRC and Health eResearch Centre (HeRC), was created to improve patient safety by reducing the number of prescription errors. Such errors occur in 5% of prescriptions according to a recent study of English general practices with one in 550 considered to be life-threatening.

Example:
SMASH and the GM Care Record
PINCER/SMASH methodology

1. Identify evidence-based medication safety indicators for primary care

2. Select most relevant indicators based on observed incidence

3. Represent selected indicators in computable form (SQL queries)

4. Embed computable indicators in feedback tool

Spencer et al., Br J Gen Practice 2014; 64(621):e181–90
Akbarov et al., Drug Safety 2015;38(7):671–82.
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Example indicators

Prescription of an oral NSAID without co-prescription of an ulcer-healing drug in a patient aged ≥65 years.

Prescription of aspirin in combination with another antiplatelet drug without co-prescription of an ulcer-healing drug.

**Prescription of a non-selective beta-blocker to a patient with asthma.**

Prescription of an oral NSAID to a patient with heart failure.

Prescription of an oral NSAID to a patient with chronic renal failure (eGFR <45)

Prescription of Amiodarone without a thyroid function test

<table>
<thead>
<tr>
<th>Indicator</th>
<th>Affected patients</th>
<th>% of eligible patients affected</th>
<th>CCG Avg (%)</th>
<th>New cases</th>
<th>Trend</th>
<th>Show on top</th>
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<td>Age≥65 no GastProt and NSAID</td>
<td>19</td>
<td>2.04</td>
<td>0.32</td>
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<td>Asthma and BB</td>
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<td>1.51</td>
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<td>0</td>
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<td>Aspirin and Antiplatelet</td>
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<td>1.11</td>
<td>7</td>
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</table>
Patients with a history of asthma who have been prescribed a β blocker

What is the risk to patients?

In susceptible patients β blockers can precipitate acute attacks of bronchospasm or worsen daily symptoms resulting in mortality or low grade morbidity respectively. The BNF advises that "β blockers should be avoided in patients with a history of asthma or bronchospasm; if there is no alternative, a cardioselective β blockers can be used with extreme caution under specialist supervision. Atenolol, bisoprolol, metoprolol, nebivolol, and (to a lesser extent) acebutolol, have less effect on the β₂ (bronchial) receptors and are, therefore, relatively cardioselective, but they are not cardiospecific. They have a lesser effect on airways resistance but are not free of this side effect". The Committee on Safety of Medicines¹ issued the following advice: "...β blockers, even those with apparent cardioselectivity, should not be used in patients with asthma or a history of obstructive airways disease, unless no alternative treatment is available. In such cases the risk of inducing bronchospasm should be appreciated and appropriate precautions taken.”

What evidence is there that this pattern of prescribing is harmful?

β blockers vary in their affinity for β₁- and β₂-adrenoceptors, and are divided into two groups, cardioselective (affinity for β₁), and non-cardioselective (affinity for β₂). The majority show little selectivity for one receptor over the other, except for bisoprolol (14-fold greater affinity for β₁-adrenoceptors) and timolol, sotalol and propranolol (26-fold, 12-fold, and 8-fold greater affinity for β₂-adrenoceptors, respectively).

Table 1: Cardioselective and non-cardioselective betablockers

<table>
<thead>
<tr>
<th>Cardioselective beta-blockers (relative selectivity for β₁-adrenoceptors)²</th>
<th>Non Cardioselective beta-blockers (relative selectivity for β₂-adrenoceptors)²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Acebutolol (2.4)</td>
<td>Labetalol (2.5)</td>
</tr>
</tbody>
</table>
SMASH – Salford roll-out

- SMASH was rolled out in 43 (out of 44) general practices in Salford (Greater Manchester, UK)
- Practices had a combined list size of 236k patients
- Roll-out started in February 2016 and was completed in August 2017
- Newly trained pharmacists were allocated to practices over time
- We used a “train the trainer” approach
What users said

“I think the main benefit is that it’s just how quick and easy it is to access these patients. Running searches on the GP clinical system is a nightmare.” (pharmacist)

“We want our pharmacist to look at the new initiations. She then sends a message to the prescribing doctor that that's a high risk prescribing area and then leave it to the doctor to decide whether to action it or not.” (GP manager)

“Having this tool depersonalises feedback. [...] It’s not ... you know, you’ve done this and I don’t think it’s safe ... it’s the system that has picked this up.” (pharmacist)

Design: Interrupted time series analysis (43 practices)

We measured outcomes during **24 months before** and **12 months after** start of the intervention

Outcome measures: Prevalence of exposure to

- any potentially hazardous prescribing (composite of 10 indicators)
- any inadequate blood-test monitoring (composite of 2 indicators)

ITSA – Aggregated results

Hazardous prescribing

6m: -27.9% [-20.3% to -36.8%]
12m: -40.7% [-29.1% to -54.2%]

Inadequate blood-test monitoring

6m: -22.0% [-0.2% to -50.7%]
12m: -23.5% [+4.5% to -61.6%]
BACKGROUND AND SIGNIFICANCE

Context of providing support for the LHS

This paper describes the design, development, and initial use of KORO in support of KGrid. KORO extends the Information Artifact Ontology (IAO) to formally define what KOs are. Hence, although the KORO is stated plainly, it specifically supports the knowledge management systems that have picked up. “Having this tool depersonalises feedback. [...] It’s not ... you know, you’ve done this and I don’t think it’s safe ... it’s the system that has picked this up.” (pharmacist)

KORO is a general formalism for a digital library component to store and manage KOs instances of computable biomedical knowledge. KGrid includes a digital platform that has picked up. "Having this tool depersonalises feedback. [...] It’s not ... you know, you’ve done this and I don’t think it’s safe ... it’s the system that has picked this up.” (pharmacist)
What is the GM Care Record?

Easy access to patient information is critical to support decision-making for health and care workers – especially in situations such as the COVID-19 pandemic. That’s where the GM Care Record comes in.

The GM Care Record supports data sharing for direct care and treatment for the city region’s 2.8m citizens. Two years tech development has been condensed into two months.

The GM Care Record means that:

- patients won’t have to keep repeating their medical history to each professional in different organisations
- care plans will be followed consistently
- clinicians will be better equipped to identify patterns and plan care more effectively to meet the patients’ needs.

The GM Care Record will contain data from:

- 444 GP practices across 10 CCGs in GM
- 10 councils
- 9 acute trusts (hospitals)
- 7 community services
- 3 mental health trusts
- 1 specialist (The Christie)

N.W. Ambulance Service, Out of Hours & 111 will also be included.

The GM Care Record supports clinical decision making by providing access to important information on:

- medications
- allergies
- test results
- care plans
- social care support
The learning health cycle of the learning health system with KGrid illustrated in Figure 2. The cycle's goal is to learn: (1) data to knowledge, (2) knowledge to practice, and (3) practice flow spanning steps 5, 6, and 7 in Figure 1. The KGrid edge as a service. Specifically, instances of the activator provide machine executable (i.e., computable) biomedical knowledge from any domain. KORO is a general formalism for a digital shared functional, computable knowledge from any domain. KORO is built upon mature and widely used technologies. However, since KORO supports practical reasoning about KOs, it has characteristics of an application ontology to some degree. Our work anticipates a future where KGrid's activator provides knowledge they hold. In this way, KGrid's activator provides knowledge findable, accessible, interoperable, and reusable.

In LHSs, after a community decides to study a problem, discrete steps are reviewed to differentiate them from KOs. Finally, the significance of knowledge objects (KOs), knowledge, KGrid allows its users to create, manage, and steward digital libraries to store and manage KOs, which are structured packages holding concepts of a KO, that serve as a formal specification for the design of KOs, and archived as an integral part of the scientific record.

For estimating individuals' lung cancer risk is developed. Then, it explains how KGrid and KOs support routine review of the lung cancer risk predictive model as a persistent resource. At step 7, the computable predictive model held in a KO is accessed and interacting with the lung cancer risk predictive model is remotely invoked by an IT system, it is applied as knowledge (step 7). This happens by combining the computable predictive model with facts about a person to generate a prediction for that person's lung cancer risk that may be actionable and potentially useful. To date, we have (c) making those means of execution available to external systems and (d) tracking the utilization of those web services. As previously described above, every KORO instance is implemented as an activator that can be called on by other systems. Early efforts to build KGrid indicate that KOs are workable and serviceable via an activator.
Conclusions
Conclusions

- The learning health system is a paradigm that blends data science, improvement science, and technology.
- It aims to capitalise on opportunities provided by the data revolution – as has happened in other industries.
- LHSs require an infrastructure consisting of people, technology, processes, and policies.
- SMASH is a learning health system for improving medication safety in primary care.
- The deployment of the GM Care Record has significantly improved the capability to develop a LHS in GM.
Thank you