School of Computing
FACULTY OF ENGINEERING

UNIVERSITY OF LEEDS

NeLL Digital Health & Care Symposium

The international fully digital symposium on digital health

AI and Patient Safety

11:15 – 11:45 CET
27th November 2020

Owen Johnson
Leeds Institute for Data Analytics
Leeds CDT for AI in Medical Diagnosis and Care
o.a.johnson@leeds.ac.uk

Outline of my talk

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PAPER KILLS
ISDH
ewt Gingrich, 2006, Capitol Hill Address

More…

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- Hello
- About Owen
- About AI
    - AI will save the world
    - AI will destroy the world
- About the data
    - It's the data dummy
    - The Tottering Tower
- A call to action
    - The AI Command Centre at Bradford
    - National strategy (UK)

About AI and Digital Health

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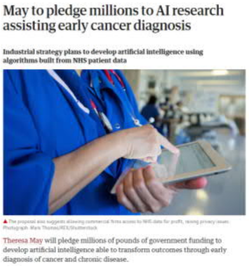
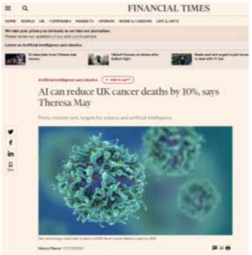


May to pledge millions to AI research assisting early cancer diagnosis

Industrial strategy plans to develop artificial intelligence using algorithms built from NHS patient data

Theresa May will pledge millions of pounds of government funding to develop artificial intelligence able to transform outcomes through early diagnosis of cancer and chronic disease.



FINANCIAL TIMES

AI can reduce UK cancer deaths by 10%, says Theresa May

"The development of ***smart technologies*** to analyse great quantities of data quickly and with a higher degree of accuracy than is possible by human beings opens up a whole new field of medical research and gives us a new weapon in our armoury in the fight against disease.
"Achieving this mission will not only save thousands of lives. It will incubate a whole new industry around AI-in-healthcare, creating high-skilled science jobs across the country, drawing on existing centres of excellence in places like Edinburgh, Oxford and Leeds – and helping to grow new ones."

www.theguardian.com/technology/2018/may/20/may-to-pledge-millions-to-ai-research-assisting-early-cancer-diagnosis

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Leeds Institute of Data Analytics

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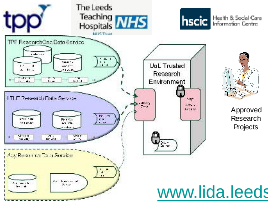
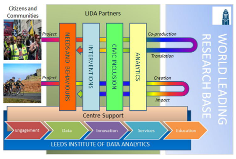
Leeds Institute of Data Analytics
Leeds MRC Bioinformatics Research Centre
Leeds ESRC Consumer Data Research Centre
£20m investment (MRC, ESRC and UoL) in Data Analytics at Leeds
Refit of the Worsley Building for 300 data scientists
ISO/ IG Accredited Safe Research Environment
High Performance Compute


tpp
The Leeds Teaching Hospitals NHS Trust
hscic Health & Social Care Information Centre
TPP ResearchOne Data Service
LTHT Research Data Service
Any Research Data Service
UoL Trusted Research Environment
Approved Research Projects

www.lida.leeds.ac.uk


Citizens and Communities
LIDA Partners
Project
Project
NEEDS AND BEHAVIOURS
INTERVENTIONS
CIVIC INCLUSION
ANALYTICS
Co-production
Translation
Creation
Impact
WORLD LEADING RESEARCH BASE
Centre Support
Engagement
Data
Innovation
Services
Education
LEEDS INSTITUTE OF DATA ANALYTICS

Centre for Doctoral Training AI in Medical Diagnosis and Care

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UK funded centre (£7m) to train 50 PhD students in AI and Medicine
Leeds University AI students embedded within Leeds Teaching Hospital

Cohort 1 (2019-2023) in LIDA with Secretary of State Baroness Morgan of Coates

Three themes where AI can be applied to advance cancer care:

- Screening and Early Detection
- Diagnosis
- Therapy and Care

e-Health Records Research Group
School of Computing

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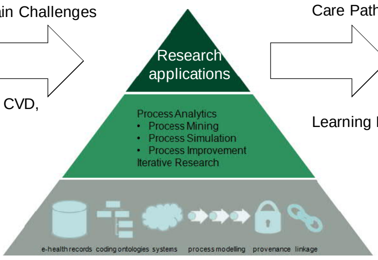
Medical Domain Challenges

Cancer, MSK, CVD,
Diagnostics,
Diabetes,
Dentistry,
etc.



Research applications

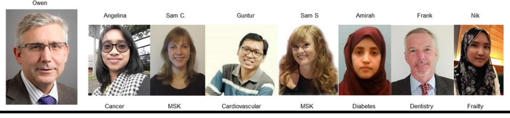
Process Analytics
- Process Mining
- Process Simulation
- Process Improvement

Iterative Research

e-health records
coding ontologies
systems
process modelling
provenance
linkage

Care Pathway Insights

Learning Health Systems


Owen
Angelina
Sam C.
Guntur
Sam S
Amirah
Frank
Nik
Cancer
MSK
Cardiovascular
MSK
Diabetes
Dentistry
Frailty

Digital Innovation Theme
Y&H NIHR Patient Safety Centre

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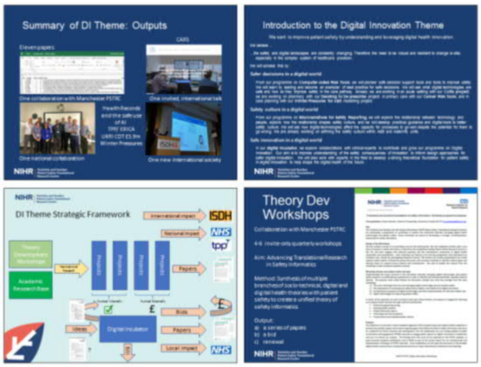
Summary of DI Theme: Outputs
Introduction to the Digital Innovation Theme
DI Theme Strategic Framework
Theory Dev Workshops
NIHR
ISDH
NHS
tpp

Let's talk…

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About AI

About AI…
"is it a robot?"

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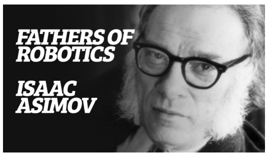
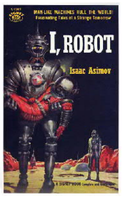

FATHERS OF ROBOTICS
ISAAC ASIMOV

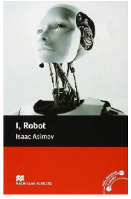
1. A ROBOT MAY NOT INJURE A HUMAN BEING OR, THROUGH INACTION, ALLOW A HUMAN BEING TO COME TO HARM.

2. A ROBOT MUST OBEY ANY ORDERS GIVEN TO IT BY HUMAN BEINGS, EXCEPT WHERE SUCH ORDERS WOULD CONFLICT WITH THE FIRST LAW.

3. A ROBOT MUST PROTECT ITS OWN EXISTENCE AS LONG AS SUCH PROTECTION DOES NOT CONFLICT WITH THE FIRST OR SECOND LAW.

—ASIMOV'S THREE LAWS OF ROBOTICS


MAN LIKE MACHINES RULE THE WORLD!
Fascinating Tales of a Strange Tomorrow
I, ROBOT
Isaac Asimov


I, Robot
Isaac Asimov

SCHWARZENEGGER
TERMINATOR 3
RISE OF THE MACHINES

About AI …
intelligence?

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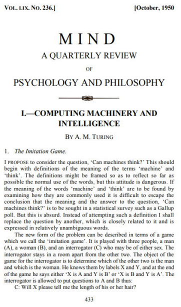
Artificial Intelligence (AI)

- intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans.
- Computers that mimic "cognitive" functions that humans associate with the human mind, such as "learning" and "problem solving".

The Turing Test (1950)

- ability to exhibit intelligent behaviour indistinguishable from that of a human.



VOL. LIX. NO. 236.] [October, 1950

M I N D
A QUARTERLY REVIEW
OF
PSYCHOLOGY AND PHILOSOPHY

I.—COMPUTING MACHINERY AND INTELLIGENCE

BY A. M. TURING

1. *The Imitation Game.*

I PROPOSE to consider the question, 'Can machines think?' This should begin with definitions of the meaning of the terms 'machine' and 'think'. The definitions might be framed so as to reflect so far as possible the normal use of the words, but this attitude is dangerous. If the meaning of the words 'machine' and 'think' are to be found by examining how they are commonly used it is difficult to escape the conclusion that the meaning and the answer to the question, 'Can machines think?' is to be sought in a statistical survey such as a Gallup poll. But this is absurd. Instead of attempting such a definition I shall replace the question by another, which is closely related to it and is expressed in relatively unambiguous words.

The new form of the problem can be described in terms of a game which we call the 'imitation game'. It is played with three people, a man (A), a woman (B), and an interrogator (C) who may be of either sex. The interrogator stays in a room apart from the other two. The object of the game for the interrogator is to determine which of the other two is the man and which is the woman. He knows them by labels X and Y, and at the end of the game he says either 'X is A and Y is B' or 'X is B and Y is A'. The interrogator is allowed to put questions to A and B thus:

C: Will X please tell me the length of his or her hair?

433

Alan, M., 1950. Turing. *Computing machinery and intelligence. Mind*, *59*(236), pp.433-460.

About AI …
is it here?

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BERNIE SANDERS:
CLINTON FOUNDATION IS A "PROBLEM"
ANOTHER GRUESOME ATTACK ON POLICE BY A BLM MOVEMENT ACTIVIST
OUR HEARTS ARE WITH THOSE 11 HEROES
HILLARY CLINTON HAS A 69 PERCENT DISAPPROVAL RATE AMONG ALL VETERANS
NO INVADERS ALLOWED
ATAN: IF I WIN CLINTON WINS!
ESUS: NOT IF I CAN HELP IT!
PRESS 'LIKE' TO HELP JESUS WIN!

www.washingtonpost.com/graphics/2017/business/russian-ads-facebook-targeting

How it works…
Artificial Narrow Intelligence (ANI)

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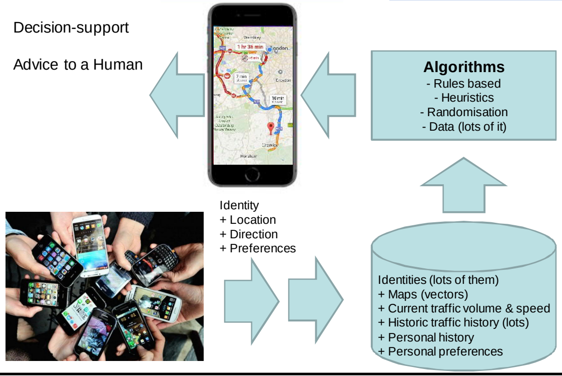

Decision-support

Advice to a Human

Algorithms
- Rules based
- Heuristics
- Randomisation
- Data (lots of it)

Identity
+ Location
+ Direction
+ Preferences

Identities (lots of them)
+ Maps (vectors)
+ Current traffic volume & speed
+ Historic traffic history (lots)
+ Personal history
+ Personal preferences

Let's talk …
About data

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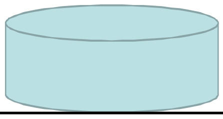
It's the data, dummy.



Infrastructure for AI

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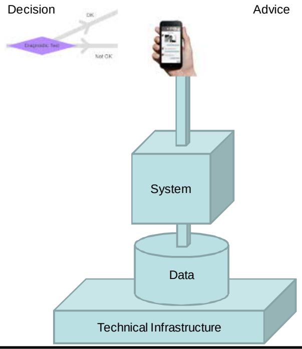

Decision
OK
Diagnostic Test
Not OK
Advice
System
Data
Technical Infrastructure

Bad AI

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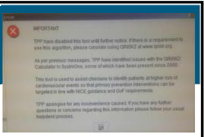
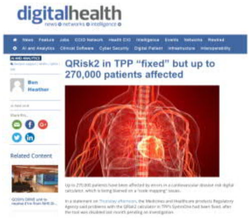


NICE Guidance 2015
Identifying patients with Cardiovascular Disease (CVD)
"People should be prioritised for assessment from an estimation of their CVD risk, based on factors already documented in electronic medical records… In order to assess CVD risk for primary prevention, GPs should use the QRISK2 risk calculator for patients up to and including 84 years of age
www.nice.org.uk/news/article/nice-recommends-wider-use-of-statins-for-prevention-of-cvd

QRISK2 was developed and tested with EMIS
But SystmOne used different Read codes

6th June 2016
Issue with QRISK2 Calculator in SystmOne
"The Medicines and Healthcare products Regulatory Agency (MHRA) has instructed TPP practices not to use the QRISK®2 Calculator in SystmOne until further notice."



digitalhealth
news networks intelligence

QRisk2 in TPP "fixed" but up to 270,000 patients affected

Ben Heather

Related Content

EHRs
are different

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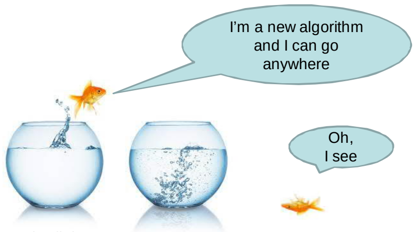

I'm a new algorithm and I can go anywhere
Oh, I see

Perfect temperature and salinity

Unknown temperature and salinity

Electronic Health Record Systems
in Yorkshire & The Humber (pop. 7m)

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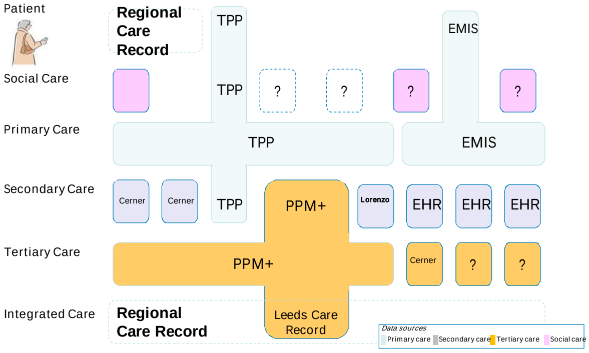

Apps/ Web sites/ PROMS/ NHS 111
Patient
Regional Care Record
TPP
EMIS
Social Care
TPP
?
?
?
?
Primary Care
TPP
EMIS
Secondary Care
Cerner
Cerner
TPP
PPM+
Lorenzo
EHR
EHR
EHR
Tertiary Care
PPM+
Cerner
?
?
Integrated Care
Regional Care Record
Leeds Care Record

Data sources
- Primary care
- Secondary care
- Tertiary care
- Social care

What we could do with AI in Digital Health

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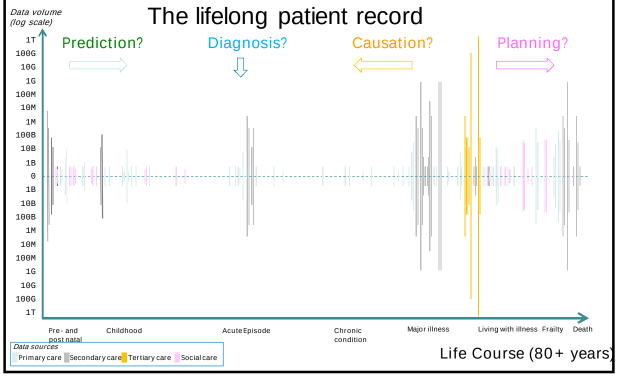
The lifelong patient record



Life Course (80+ years)

Data Quality
Multi-modal High Variety and Veracity

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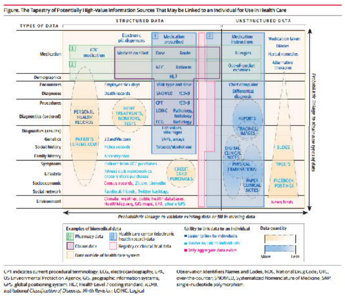
Figure. The Tapestry of Potentially High-Value Information Sources That May be Linked to an Individual for Use in Health Care
TYPES OF DATA
STRUCTURED DATA
UNSTRUCTURED DATA
Medication
Demographics
Encounters
Diagnoses
Procedures
Diagnostics (ordered)
Diagnostics (results)
Genetics
Social history
Family history
Symptoms
Lifestyle
Socioeconomic
Social network
Environment
Probabilistic linkage to validate existing data or fill in missing data
Probabilistic linkage to obtain new types of data

Weber GM, Mandl KD, Kohane IS. Finding the Missing Link for Big Biomedical Data. *JAMA*. Online May 22, 2014. doi:10.1001/jama.2014.4228.

Weiskopf, N.G. and Weng, C., 2013. Methods and dimensions of electronic health record data quality assessment: enabling reuse for clinical research. *Journal of the American Medical Informatics Association*, *20*(1), pp.144-151.

Table 1 Terms used in the literature to describe the five common dimensions of data quality

Completeness	Correctness	Concordance	Plausibility	Currency
Accessibility	Accuracy	Agreement	Accuracy	Recency
Accuracy	Corrections made	Consistency	Believability	Timeliness
Availability	Errors	Reliability	Trustworthiness	
Missingness	Misleading	Variation	Validity	
Omission	Positive predictive value			
Presence	Quality			
Quality	Validity			
Rate of recording				
Sensitivity				
Validity				

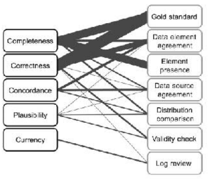
Completeness
Correctness
Concordance
Plausibility
Currency
Gold standard
Data element agreement
Element presence
Data source agreement
Distribution comparison
Validity check
Log review

Figure 1 Mapping between dimensions of data quality and data quality assessment methods. Dimensions are listed on the left and methods of assessment on the right, both in decreasing order of frequency from top to bottom. The weight of the edge connecting a dimension and method indicates the relative frequency of that combination.

Data Quality
- a forensic inspection

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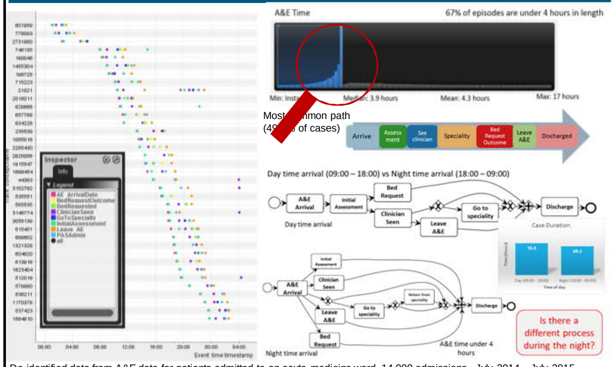
A&E Time
67% of episodes are under 4 hours in length
Min: Insta
Median: 3.9 hours
Mean: 4.3 hours
Max: 17 hours
Arrive
Assess ment
See clinician
Speciality
Bed Request Outcome
Leave A&E
Discharged
Inspector
Info
Legend
AE_ArrivalDate
BedRequestOutcome
BedRequested
ClinicianSeen
GoToSpecialty
InitialAssessment
Leave_AE
PASAdmin
all
A&E Arrival
Initial Assessment
Bed Request
Clinician Seen
Go to speciality
Leave A&E
Discharge
Day time arrival
Case Duration
Night time arrival
A&E time under 4 hours
Event time timestamp

Most common path
(49.6% of cases)

Day time arrival (09:00 – 18:00) vs Night time arrival (18:00 – 09:00)

Is there a different process during the night?

De-identified data from A&E data for patients admitted to an acute medicine ward, 14,000 admissions - July 2014 – July 2015

Data Quality
- a forensic inspection

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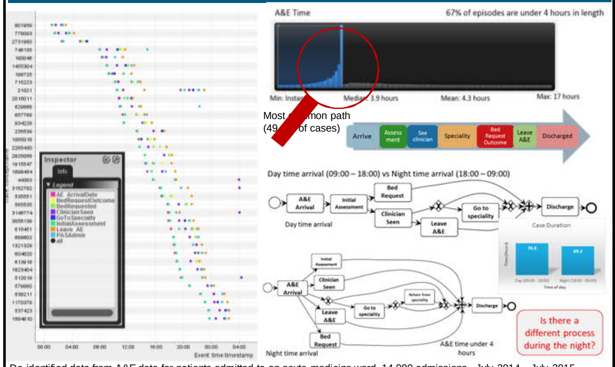
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Inspector
Info
Legend
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Initial Assessment
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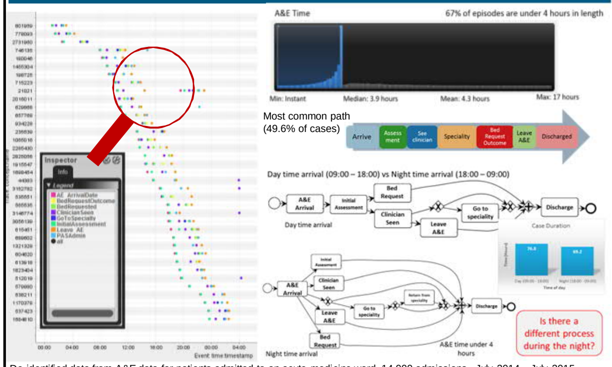
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Speciality
Bed Request Outcome
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Discharged
Inspector
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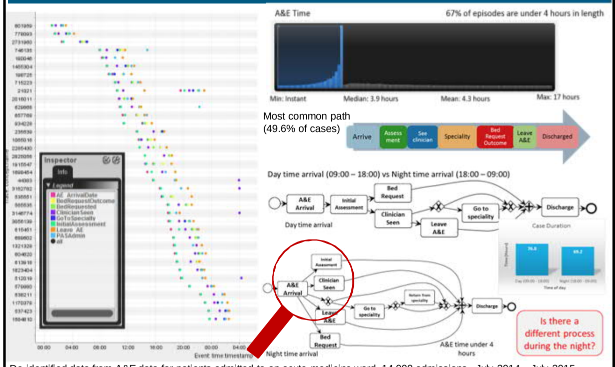
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Cause and effect
Change => change => …

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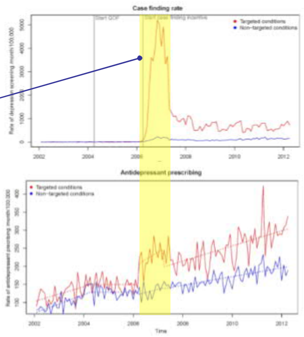
Figure 1 Rates of coded case finding for depression in patients with conditions targeted or not by incentivised case finding, 2002–2012.

Period of targeted financial incentive scheme

Figure 3 Rates of new antidepressant prescribing in patients with conditions targeted or not by incentivised case finding, 2002–2012.



65 Leeds GP Practices using SystmOne

McLintock K, Russell AM, Alderson SL, West R, House A, Westerman K, Foy R. The effects of financial incentives for case finding for depression in patients with diabetes and coronary heart disease: interrupted time series analysis. *BMJ Open* 2014;4:e005178. doi: 10.1136/bmjopen-2014-005178
Available from: http://eprints.whiterose.ac.uk/81056

Electronic Health Records Change

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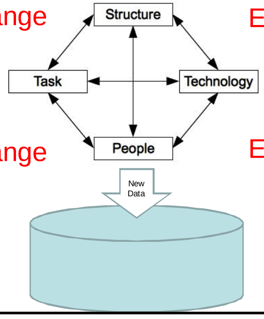
Data in Electronic Health Record (EHR) Systems is generated as the output of a complex interplay of four forces that are always changing and always affecting each other in non-linear ways.



Endless Change

Endless Change

Endless Change

Endless Change

Structure

Task

Technology

People

New Data

Leavitt Diamond (1965)

The "Tottering Tower" of AI in Health

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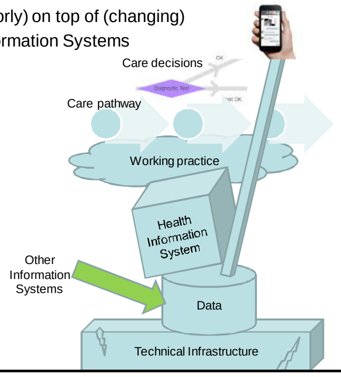
AI sits (poorly) on top of (changing) Health Information Systems



Care decisions

Care pathway

Working practice

Health Information System

Other Information Systems

Data

Technical Infrastructure

Let's talk…

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A call to action.

Three AI threats to Patient Safety

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1) The Health Information Systems that an AI sits on are not constants, in fact they are highly variable.

2) Historical data that AI is trained on has bias that machines can (and will) learn to replicate.

3) The smartest AI can self-learn so will evolve beyond our comprehension (and therefore beyond regulation?).

AI Command Centre at Bradford Teaching Hospitals

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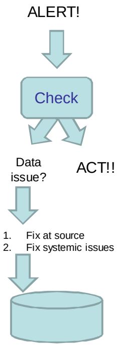
Europe's first AI-powered hospital command centre

NHS
Bradford Teaching Hospitals
NHS Foundation Trust

Command Centre

https://uscan.gehealthcarepartners.com/insight-detail/what-makes-the-ge-healthcare-command-center-soluti



ALERT!

Check

Data issue?

ACT!!

1. Fix at source
2. Fix systemic issues

Learning Health Systems

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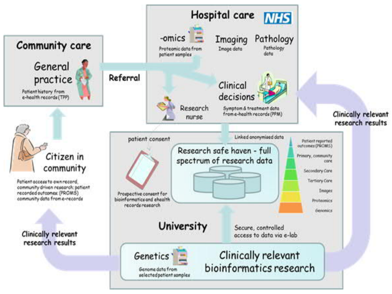
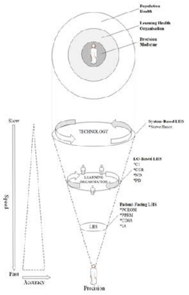

Hospital care
NHS
-omics
Proteomic data from patient samples
Imaging
Image data
Pathology
Pathology data
Community care
General practice
Patient history from e-health records (TPP)
Referral
Clinical decisions
Research nurse
Symptom & treatment data from e-health records (PPM)
Clinically relevant research results
Citizen in community
Patient access to own record, community driven research: patient recorded outcomes: (PROMS) community data from e-records
patient consent
Linked anonymised data
Research safe haven - full spectrum of research data
Patient reported outcomes (PROMS)
Primary, community care
Secondary Care
Tertiary Care
Images
Proteomics
Genomics
Prospective consent for bioinformatics and ehealth records research
University
Secure, controlled access to data via e-lab
Clinically relevant research results
Genetics
Genome data from selected patient samples
Clinically relevant bioinformatics research


Population Health
Learning Health Organisation
Precision Medicine
Slow
Speed
Fast
Accuracy
TECHNOLOGY
System-Based LHS
*Surveillance
LEARNING ORGANISATION
LO-Based LHS
*CI
*CER
*ND
*PD
Patient-Facing LHS
*PCROM
*PPRM
*CDSS
*IA
LHS
Precision

McLachlan S, Potts HW, Dube K, Buchanan D, Lean S, Gallagher T, Johnson O, Daley B, Marsh W, Fenton N.
The Heimdall framework for supporting characterisation of learning health systems. Journal of Innovation in Health Informatics. 2018;25(2):77-87.

UK NHS Plans for AI

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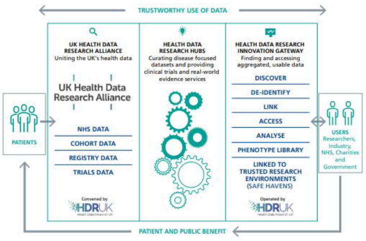
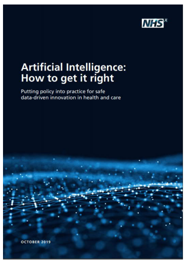

TRUSTWORTHY USE OF DATA
PATIENTS
UK HEALTH DATA RESEARCH ALLIANCE
Uniting the UK's health data
UK Health Data Research Alliance
NHS DATA
COHORT DATA
REGISTRY DATA
TRIALS DATA
Convened by HDRUK
HEALTH DATA RESEARCH HUBS
Curating disease focused datasets and providing clinical trials and real-world evidence services
HEALTH DATA RESEARCH INNOVATION GATEWAY
Finding and accessing aggregated, usable data
DISCOVER
DE-IDENTIFY
LINK
ACCESS
ANALYSE
PHENOTYPE LIBRARY
LINKED TO TRUSTED RESEARCH ENVIRONMENTS (SAFE HAVENS)
Operated by HDRUK
USERS
Researchers, Industry, NHS, Charities and Government
PATIENT AND PUBLIC BENEFIT



NHSX

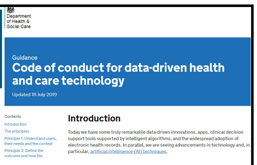
Artificial Intelligence:
How to get it right

Putting policy into practice for safe data-driven innovation in health and care

OCTOBER 2019

https://www.nhsx.nhs.uk/assets/NHSX_AI_report.pdf

UK NHS Code of Conduct



Department of Health & Social Care

Guidance

Code of conduct for data-driven health and care technology

Updated 18 July 2019

Contents
Introduction
The principles
Principle 1: Understand users, their needs and the context
Principle 2: Define the outcome and how the

Introduction

Today we have some truly remarkable data-driven innovations, apps, clinical decision support tools supported by intelligent algorithms, and the widespread adoption of electronic health records. In parallel, we are seeing advancements in technology and, in particular, artificial intelligence (AI) techniques.

1. Understand users, their needs and the context.
2. Define the outcome and how the technology will contribute to it.
3. Use data that is in line with appropriate guidelines for the purpose for which it is being used.
4. Be fair, transparent and accountable about what data is being used.
5. Make use of open standards.
6. Be transparent about the limitations of the data used.
7. Show what type of algorithm is being developed, or deployed, the ethical examination of how the performance will be validated, and how it will be integrated into health and care provision.
8. Generate evidence of effectiveness for the intended use and value for money.
9. Make security integral to the design.
10. Define the commercial strategy.

www.gov.uk/government/publications/code-of-conduct-for-data-driven-health-and-care-technology/initial-code-of-conduct-for-data-driven-health-and-care-technology

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AI and Patient Safety

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- The next five years will see a rapid adoption of AI technologies in diagnostic pathways that hold the promise of faster, cheaper, more effective diagnosis to enable personalised care pathways and treatment.
- AI will get things wrong and make mistakes.
- There are a range of patient safety risks that may emerge as unintended consequences of AI.
- The digital health community is increasingly aware that it must warily embrace AI but a mature discussion on patient safety issues is needed urgently.

It is time for that mature discussion…

School of Computing
FACULTY OF ENGINEERING

UNIVERSITY OF LEEDS

NeLL Digital Health & Care Symposium

The international fully digital symposium on digital health

27th November 2020

AI and Patient Safety

11:15 – 11:45 CET

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Leeds CDT for AI in Medical Diagnosis and Care
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