

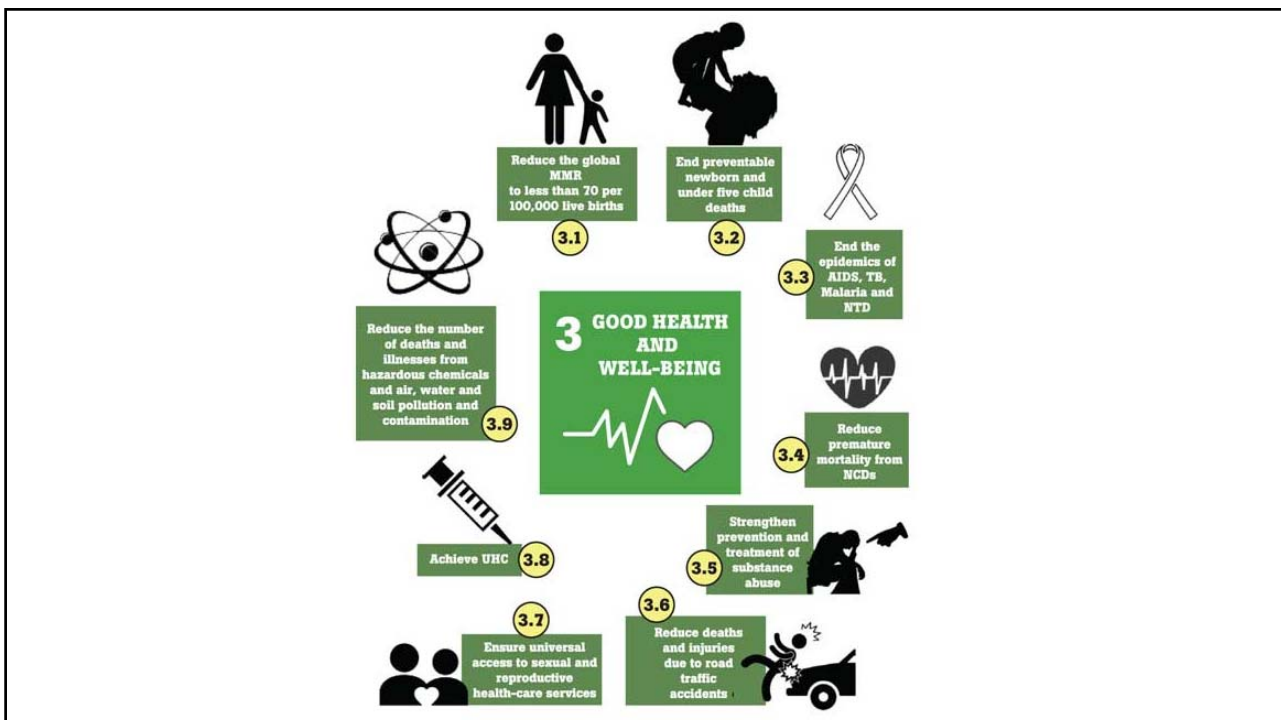
The promise of AI: Transforming health systems from reactive to predictive, preventative and high performing ?

Anne Johnson

Vice-President – International, UK Academy of Medical Sciences

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Artificial Intelligence and the digital revolution for health:

Genomics



Artificial intelligence and robotics



Digital medicine



Organisational development



#TopolReview www.hee.nhs.uk/our-work/topol-review

Where AI can improve health and care

Artificial Intelligence

Now DeepMind's AI can spot eye disease just as well as your doctor

The AI from Google's DeepMind made correct diagnoses 94.5 per cent of the time in a trial with Moorfields Eye Hospital

- Operational improvement (smart health systems)
- Diagnosis of disease (e.g. retinal imaging, breast cancer screening)
- Treatment (e.g. assisting with treatment decisions or AI as a treatment itself, for example chatbots to support mental health)
- Prevention (e.g. machine learning algorithms to optimise modifiable risk, behavioural interventions, or preventing disease outbreaks)

Narrative of AI in global health is just beginning

Also in high resource settings

Deep learning enabled by massive quantities of data, greater computing power & cloud storage



AI is beginning to have an impact for

- **Clinicians**, mainly through rapid accurate image interpretation and clinical decision support systems
- **Health systems** through improved efficiencies and costs by enhancing workflow, reducing medical errors, predicting clinical outcomes or monitoring epidemics
- **Patients**, enabling them to process their own data to promote health

In low resource settings

advances in digital technologies are putting the **basics** in place **for AI in health to expand**, with

- strong mobile phone penetrations and mHealth applications
- substantial investments in digitizing health information and in cloud computing
- increasing broadband coverage

Ann Aertz, Novartis Foundation

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Current challenges for AI in global health

High promise, little science



Risk for exacerbating inequities – use of AI can widen existing inequities, e.g. through a lack of inclusion in datasets, lack of access (digital exclusion)



Iatrogenic risk – of faulty algorithms with potential harm to patients. Who takes the blame? (Company, clinician, health care system)



Security and privacy – future of AI in medicine rests with how well privacy, security, safety, reliability and ownership of data can be assured, with existing risk of deliberate hacking of algorithms. Public Trust is key.



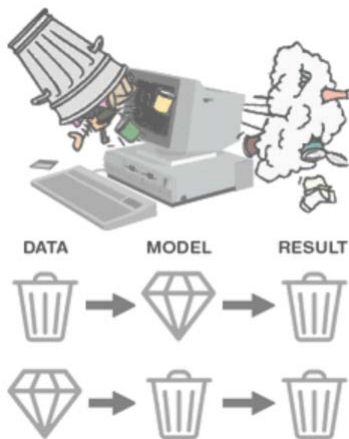
Little prospective validation – for tasks that machines could perform. Clinical validity alongside health systems research and economic validation



Lack of transparency- the black box of models and algorithms where it is impossible to understand the determination of the output

Adapted from Ann Aertz, Novartis Foundation

Garbage in Garbage out? Availability of high quality digital clinical records at scale to train machine learning and clinical AI remains a major challenge (the phenotype)



More poor quality and incomplete data (and especially biased data) won't necessarily fix the problem. Good data requires time, money and professional capacity

Whose data is it anyway?

Representativeness
Ownership
Public trust

Who gets the blame then the diagnosis is wrong?

The computer
The company
The clinician?



The Topol Review: UK 2019

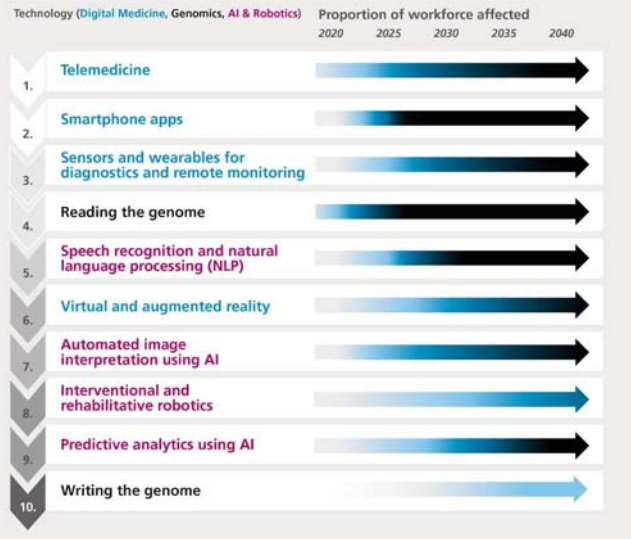
'This Review proposes **three principles** to support the deployment of digital healthcare technologies throughout the UK National Health Service:

1. Patients included as partners and informed about health technologies
2. The healthcare workforce needs expertise and guidance to evaluate new technologies, grounded in real-world evidence.
3. The gift of time: wherever possible the adoption of new technologies should enable staff to gain more time to care '

Are these transferrable principles? Are there novel opportunities for 'leapfrogging' in LMICs where there are major skills shortages?



Top technologies



Arrow heat map represents the perceived magnitude of impact on current models of care and, by inference, on the proportion of workforce affected.

- <20%
- 50%
- 80%
- >=80%

Digital Revolution

Connecting and empowering people across the world



- 7 billion**
Global mobile phone subscriptions
- 3 billion**
internet users
– mobile overtaken fixed devices
- 72% people**
search for health information online
- 500 million**
Tweets per day (80% on mobiles)
- 100 billion**
apps downloads from Apple
Apps Store
- 11.1 trillion**
Economic impact (\$) p.a. of IoT by 2025

REVIEW

<https://doi.org/10.1038/n41598-019-0956-2>

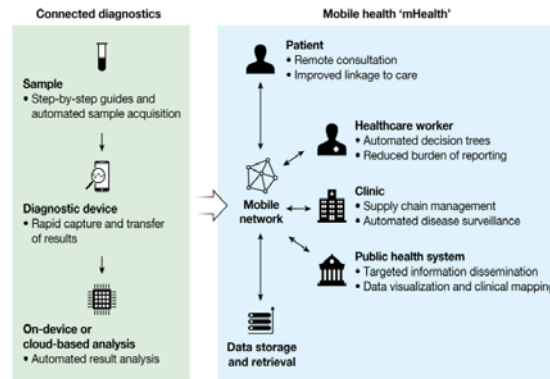
Taking connected mobile-health diagnostics of infectious diseases to the field

Christopher S. Wood^{1,2,3,4,5,6,7}, Michael R. Thomas^{1,2,3,4,5}, Jobie Buckle⁶, Tivani F. Mashamba-Thompson⁶, Kobus Herbst⁷, Deenan Pillay⁸, Rosanna W. Peeling⁹, Anne M. Johnson¹⁰, Rachel A. McKenzie⁹ & Molly M. Stevens^{1,2,3,4*}



Fig. 2: Deploying an mHealth connected diagnostic.

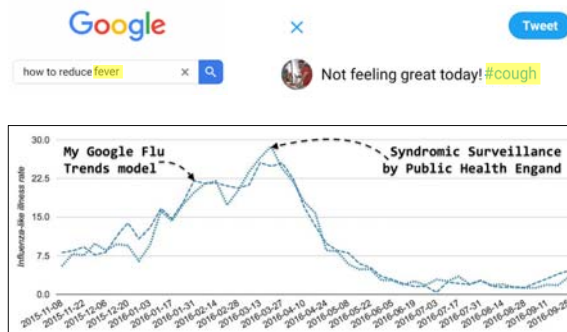
From: Taking connected mobile-health diagnostics of infectious diseases to the field



Using social media and search queries to track and respond to flu-like illness



i-sense



- Algorithm trained on **Google search data** showed Pearson correlation of **0.96** compared to data from the Royal College of General Practitioners
- **Outbreak detection 4 days earlier** than traditional surveillance
- i-sense Flu algorithms now **adopted by Public Health England for national flu surveillance** and used in most recent annual flu report

Wagner, M., Lampos, V., Cox, I. J., and Pebody, R. 'The added value of online user-generated content in traditional methods for influenza surveillance.' *Scientific Reports* (2018)



7.3.5 Speech recognition (Example 5 in Figure 1 – Chapter 3): South Tees Hospital NHS Foundation Trust Accident and Emergency

South Tees Hospital NHS Foundation Trust A&E department introduced clinical speech recognition as a way of dealing with the rising volume of clinical documentation resulting from increasing patient numbers. The technology improved the ease and speed with which clinical documentation

was completed, as well as the quality of documentation. When compared with handwriting, typing or traditional dictation, the technology was found to save three minutes per patient, freeing up vital time for clinicians in A&E to see and treat patients.¹³⁶

Each year there are approximately

24 million
A&E attendances¹³⁷

63 million
outpatient
attendances¹³⁸

340 million
GP consultations¹³⁹

Using a conservative estimate of

one minute
saved per patient
consultation



Annually, that equates to approximately

400,000
hours of A&E
consultation time



230
A&E doctors'
time back for
clinical care

one million
hours of outpatient
clinic time



600
hospital doctors'
time back for
clinical care

5.7 million
hours of GP
consultation time



3200
GPs' time back
for clinical care

Use case: Automatic image interpretation

Case: Breast cancer screening

The standard is a double reading of mammograms by two experts, which improves accuracy. However, there are too few experts available to meet demand

Solution

Software is helping radiologists detect breast cancer by using deep learning to act as an independent reader. It also potentially increases the accuracy of screening by reducing the number of false positives and negatives.

Outcome

The software has received CE marking and is undergoing clinical trials in an NHS Test Bed and across Europe.



7.3.6 Automated image interpretation (Example 7 in Figure 1 – Chapter 3): Diagnostic support in Radiology

Automatic image interpretation using deep learning for the automated detection of breast cancer has been described as a use case in Chapter 3. The aim is to improve the accuracy of screening while benefiting the workforce by eliminating the need for a second reader of the mammography scans.¹⁴⁰

Radiologists conservatively spend at least

60%

of their time reviewing images.¹⁴¹



Eliminating the need for a second reader represents a

30%

reduction in the time spent reviewing mammograms.



If we assume that what has been achieved with mammography can also be applied to a large extent to other medical images reviewed by radiologists, **AI methods such as deep learning have the potential to reduce the time radiologists spend reviewing images by**



20%¹⁴¹



Each year there are approximately

41 million

medical images taken and read by the UK NHS workforce of

4,204

radiologists.^{142, 143}

Annually, the potential impact of AI technologies on diagnostic radiology equates to the equivalent of approximately



8.2 million
images



890,000
hours of
radiologist time



500
radiologists' time back
for clinical care

Looking to the future: Interventional robotics

Scenario: Colonoscopy

Robotic colonoscopy, under development at the University of Leeds and next to first-in-human trials, is designed to be painless and extremely easy to perform.

Roles/functions change

- AI augmentation allows staff (eg primary care clinicians) to perform procedures
- Can be performed by clinicians in the community without anaesthetic cover or support



Use case: Mental health triage bot

Case: Speech recognition and natural language processing (NLP)

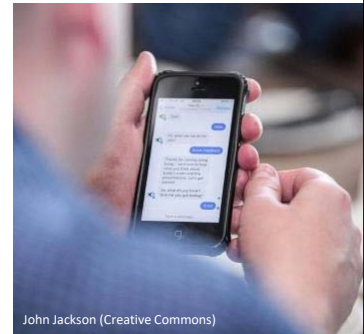
Patients with acute clinical concerns over their mental health often struggle to access services

Solution

An NLP-enabled mental health triage bot has been created, which analyses text and voice inputs for emotion and suicidal ideation and is to be built in to the GP IAPT pathway

Outcome

AI-powered bot is constantly available to patients and negates the need for travel. For clinicians, the bot saves approximately one hour of their time per patient.



John Jackson (Creative Commons)

Looking to the future: Predictive analytics

Scenario: AutoPrognosis framework

Predictive analytics, based on machine learning, can provide more accurate predictions than clinical risk scores.

It can automatically discover the relevant risk factors and automatically makes design choices on which algorithms to use.

Roles/functions change

- As predictive analytics are increasingly used and embedded in the electronic patient record, their use will become more ubiquitous.
- They can be used by clinicians to better diagnose the patient at hand and by healthcare policy makers to enhance and individualise screening programmes.



Challenges for implementation

- High quality data and supporting infrastructure
- Interdisciplinary collaboration
- Co-production with patients
- Workforce skills – training and career
- Clinical testing and cost-effectiveness. Who determines priorities and where?
- Accountability of the technology
- Regulation
- Interoperability
- Relationship with industry (markets)

Role of Academies in AI development

- Breadth of multi-disciplinary expertise
- International collaboration
- Independent, authoritative voice
- Training, sharing experience, role of young academy (eg GCRF /IAP Phillipines)
- Convening power - public groups and stakeholders
- Review and deploy the evidence as well as making recommendations or developing principles
- Horizon scanning and debate/address upcoming challenges

Recent work in the UK

- **UK Government and Parliament**
 - AI in the UK: Ready, willing, able? (2018) – House of Lords Select Committee Algorithms in decision-making (2017) – House of Commons S&T Committee
 - Growing the artificial intelligence industry in the UK (2017) – BEIS and DCMS
 - The big data dilemma (2016) – House of Commons S&T Committee
- **Academy of Medical Royal Colleges** - Artificial Intelligence in Healthcare (2019)
- **Health Education England** - Preparing the healthcare workforce to deliver the digital future. Topol Review (2019)
- **Royal Academy of Engineering** - Towards trusted data sharing: guidance and case studies (2018)
- **Academy of Medical Sciences** - Our data driven future in healthcare (2018)
- **Turing Institute** - Growing the national institute for data science and artificial intelligence (2018)
- **IPPR** - The Lord Darzi review of health and care: Interim report (2018)
- **Royal Society** - Machine learning: the power and promise of computers that learn by example (2017)