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AI IN HEALTHCARE

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1. A 2020 snapshot

Early uses of Artificial Intelligence to aid decision-making in healthcare date back to the 1970s, but their scope was limited by data availability, data processing power, and reliance on logical systems programmed by humans. The decade leading up to 2020 saw an explosion of interest and investment in new healthcare AI when it became clear that machine learning methods could solve complex problems by creating sophisticated new algorithms, quite different from those that could be developed with expert, logic-based programming.

By 2017, AI for healthcare was a major goal in the UK's industrial strategy, with investment in 2018 focused on centres of excellence in diagnostic imaging and pathology. This was followed by broader strategies addressing the wider scientific, commercial, organisational, skills, and regulatory changes needed to realise the potential of AI and digital health; and the formation of NHSX in 2019. Already in 2017 a few products using AI (e.g. Heartflow in cardiology), were supported for general use in the NHS.

Artificial Intelligence is an umbrella term for a range of techniques that can improve patient care and healthcare efficiency in areas including: automated analysis of complex data such as images, speech, and movement; improving diagnosis and professional decisions on treatment; controlling healthcare robotics and assistive devices; personalising day-to-day support for patients, or improving the efficiency of core processes, such as appointments, logistics and record-keeping.

"Artificial Intelligence: How to get it right" [1], an October 2019 NHSx report (55 pages) provides a strategy for ensuring healthcare and the wider economy make the most of these opportunities. It also sets out the challenges in AI, the NHS, policy and regulation that need to be addressed.

A UK Government Policy Paper Data saves lives: reshaping health and social care with data [2] highlighted the central role of robust, trustworthy and clear data governance, access and analysis in enabling life-saving research during the COVID 19 pandemic, and in improving healthcare for the future – for both conventional analysis and AI. It also highlighted the value of Privacy Enhancing Technologies (PETs) such as synthetic data, homomorphic encryption and federated machine learning in opening up more opportunities. The accompanying paper on **AI Basics** covers some of these techniques.

"AI and Healthcare" [3], a December 2020 briefing by the Parliamentary Office of Science and Technology is a shorter summary of the technical, societal, ethical and legal issues.

To complement these, this brief summarises how far healthcare AI products had progressed towards use by 2020 and illustrates progress in a few areas. The brief draws on a range of sources, where possible using peer-reviewed systematic reviews.

Although few AI-based healthcare products are in large-scale use, progress can be tracked through:

1. early-phase clinical trials on the effectiveness of products
2. regulatory approval to put products on the market – UKCA or CE marking, or FDA approval
3. evidence of readiness for larger scale use from late-stage trials, or guidance from NICE or other independent bodies.

Of these, marketing approvals provide perhaps the most complete picture.

AI-based products with marketing approval in 2020

A 2021 paper by Muehlematter et al [4] analysed all the marketing approvals for AI/ML-based medical devices between 2015 and 2020 in the regulatory systems of all the EU countries (then including the UK) and the USA's FDA.

AI-based software usually forms part of a larger system or device, and manufacturers can choose to give a lot of publicity to a small AI contribution in the product, or vice versa. While this paper identified 222 devices approved in the USA (240 in Europe), another analysis [5], covering FDA approvals 2010-2020 but using a more cautious definition identified only 64 products. Mapping application areas can also be subjective: Mammography products could fall under the radiology or oncology categories. It is also important to remember that some approved products are not actively marketed yet.

Nevertheless, both analyses showed similar patterns.

- Most approved products to date are based on image analysis, including radiology and ophthalmology. After radiology, the most common applications are in general medicine, cardiology and neurology.
- There has been a rapid acceleration in the number of new products approved each year, increasing from >10 in the EU in 2015 to 100 by 2019 [4].
- Most products in the USA and Europe are from smaller companies, which may influence the way long, costly clinical evaluations are done.
- A high proportion of AI/ML-enabled devices are specified for lower-risk tasks, falling into EU Class I or Class IIa (~90% of non-IVD devices). Products in higher risk classes (30) in the EU mainly came from the USA, Germany, France, Israel and Sweden.

Application area	EU and UK approvals to 2020 Ref [4], Muehlematter et al	Task Example
Radiology	115 products (55%)	• Bone fracture detection from X-rays (Gleamer, France) • Mammogram Breast Cancer identification support (JLK Inspection, South Korea, Kheiron, UK, Siemens and others) • Workflow improvement for cardiovascular ultrasound imaging (GE Medical Systems, USA) • Lung disease detection from chest X-rays (Oxipit, Lithuania)
General	29 products (14%)	• Asthma remote monitoring and management (Respiri, Australia) • Medical data interpretation support (diagnostic lab reports and other sources) (Medicus, Austria) • Pulmonary function test interpretation support (Artiq, Belgium)
Cardiovascular	23 products (11%)	• Remote patient monitoring (Huma, UK) • Detection of heart murmurs (CSD Labs, Austria) • ECG in identifying atrial fibrillation and other conditions (Apple, USA) • Assessing fractional flow reserve non-invasively from CT images (Heartflow, USA)
Neurology	19 products (9%)	• Control of upper limb prosthesis (Coapt, USA) • Early-stage dementia diagnosis with cognitive tests (Cognetivity Neurosciences, UK)
Ophthalmology	11 products (5%)	• Glaucoma hemifield test support tool (Carl Zeiss, Germany)
Pathology	7 products (3%)	• Cancer recognition in prostate needle biopsies (Ibex Medical, Israel)
Gastroenterology	5 products (2%)	• Colonoscopy polyp detection support (Fujifilm Europe, Germany)
Microbiology	2 products (1%)	• Urine culture plate imaging and interpretation (Clever Culture Systems, Switzerland)
Other areas		• Insulin dosing decision support (DreaMed Diabetes, Israel)

There are currently 301 active or recruiting clinical trials being conducted worldwide that include the term 'machine learning' listed on the US National Library of Medicine database.

Within the UK, current clinical trials show steadily widening uses in radiology and image-analysis, and newer use cases in areas such as surgery, decision support, and early diagnosis. Examples include:

- The use of vital sign monitoring and deep learning techniques to identify patients with COVID-19 in hospital wards that are deteriorating earlier than current measures. (The Christie NHS Foundation Trust) [6]
- Application of GoSurgery software to produce standardised surgical workflows using AI computer vision to automatically recognise steps during surgery and automatically present workflows. (Imperial College Healthcare Trust) [7]
- Identifying amyloid-specific cognitive impairment in patients with early Alzheimer's disease using the analysis of acoustic and linguistic speech patterns. (Novoic Ltd.) [8]
- Identifying inflamed terminal ileum in patients with Crohn's disease. (London North West Healthcare NHS Trust) [9]
- Evaluating the usefulness of DERM algorithm for identifying Basal Cell Carcinoma and Squamous Cell Carcinoma from skin lesion images. (Chelsea and Westminster Hospital) [10]
- Identifying abnormalities from routine clinical care and research volunteer head scans. (King's College Hospital NHS Trust) [11]

2. Radiology

The effectiveness of AI-based image analysis (mainly using CNNs), and the rapid growth in demand for radiological imaging which far exceeds the expansion of trained staff, has made radiology the fastest growth area for AI-based medical products [12].

Large scale screening programmes (breast mammograms, lung/thorax scans etc.) create vast volumes of images to be inspected for disease signs and even small gains in performance or efficiency can be highly valuable. There is a range of potential benefits from AI (Fig. 1), both in low-risk and high-risk product classes - such as:

- Offloading relatively straightforward tasks, such as segmenting images and measuring regions and features of interest (left ventricle, heart wall thickness, scar tissue etc.)
- Improving workflow efficiency by reducing radiologist workloads
- Improved detection and classification accuracies
- Automatic registration of multiple images taken at different time points to quantify changes (e.g. tumour growth rate)
- Improving image acquisition times and image quality through image reconstructions, removal of artefacts and missing data corrections
- Real-time guidance during ultrasound
- Multimodal image registration for improved tumour evaluation (PET-MRI, PET-CT)

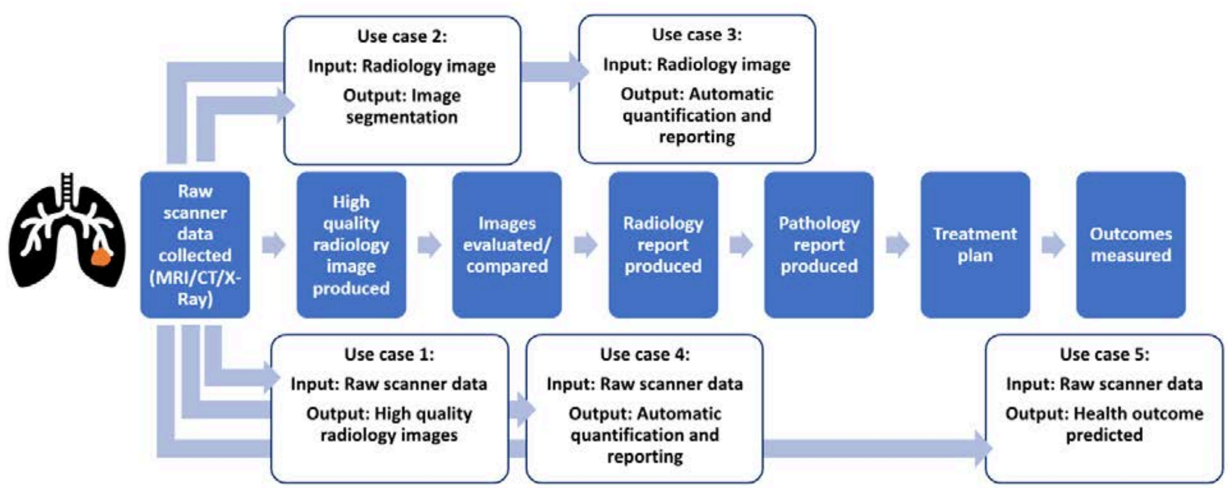

Fig. 1: Radiology workstreams and areas of potential AI applications.

Alongside the 100+ regulatory clearances/approvals for AI products in radiology, there is excellent evidence that well designed AI can match expert human performance in many areas, including diagnostic classification [13].

We are not yet seeing widespread use in routine health care, although even limited uptake and use in radiology can mean AI-based analysis of millions of scans worldwide. The evidence needed to drive wider uptake – from larger longer-term trials, comparative studies, and analyses of cost-effectiveness and health economics – has been slower to develop.

Nagendran et al [14], highlighted the limited scope, the potential for bias, and inadequate reporting of many studies. Between 2012 and 2019, only two randomized high-quality clinical trials in AI were published in medical imaging, although a further eight were in progress. The remaining 81 clinical studies were not randomised, were mostly retrospective, and had a higher risk of bias in their design. Out of the nine prospective trials, only six studies including validation in a real-world clinical setting.

Nevertheless, by 2020, more complete clinical trials and cost evidence started to be published. For example, Salim et al [15] published the first independent head-to-head comparison of three AI mammography readers, and found that the best of the three AI products had sensitivity in cancer detection (81.9%) superior to a single human reader (77.4%) and similar to a second reader (80.1%) at the same specificity.

Case study 1: Improving Chest X-ray screening - product evaluation and uptake

In the UK alone, there were 47,838 new cases of lung cancer between 2015 and 2017, making it the third most common cancer type [16]. Approximately, 75% of lung cancers are detected at a late stage, but screening can aid in the early identification of pulmonary nodules that pose risks.

Aidence, a company based in the Netherlands, was granted the CE mark in 2017 for a product called Veye Chest (now called Veye Lung Nodules; MDR, 2017/745) than can automatically identify and classify solid and sub-solid pulmonary nodules from CT scans [17]. This stand-alone software integrates into the current PACS, automatically analysing each new CT scan as it is opened and sending results directly to the PACS. It is classified as a Class IIb device and is currently in use in at least 10 UK and European sites. Alongside the identification and classification features, the software also compares new CT chest scans to previous scans from the same patient and determines the growth rate of nodules over the time.

The AI development involved algorithm training on 45,000 chest CT scans from the National Lung Screening Trial dataset, with validation studies performed at the University of Edinburgh in collaboration with Aidence and published as conference posters [18]. A small retrospective validation study was performed in 2019 on 337 chest CT scans from 314 people using the Lothian NHS database. The inclusion criteria were age 50-74, and a previous history of smoking, or currently smoking, or have radiological evidence of pulmonary emphysema – the validation did not cover other patient groups. In the data set Veye Chest successfully segmented 95% of the 428 pulmonary nodules between ≥3mm and ≤30mm, with performance comparable to experienced radiologists. The mean inter-reader dice coefficient[1] was 0.86 (95% CI: 0.51, 0.95) between the segmentations produced by the radiologists and Veye Chest.

[1] The Dice coefficient is a measure of the similarity between two samples, that is commonly used to assess the similarity between image segmentations.

In 2021, NICE published a technology briefing on "AI for analysing chest CT images", which discussed Veye Chest and two other chest CT-based AI software products [19]. Both icolung (icometrix (Class I)) and Veolity (MeVis (Class IIa)) can also be used for automatic detection, segmentation, and measurement of lung abnormalities.

NICE's briefing concluded there was currently limited evidence for using AI for chest CT. Whilst the evidence for Veye Chest was stronger than for others, it only assessed a small sample from a single population [19].

The NICE briefing also highlighted the challenge of assessing the full costs and benefits of deploying the technology in the NHS. The expert commentators were positive about the potential to improve diagnostic accuracy, reduce reporting times and reduce the chance of missing early-stage lung cancer or metastases. It was also noted that the radiology workflow could be improved whereby software could provide the first reading, replacing the need for a second radiologist reader, and reduce interobserver and intraobserver variability. However, the uncertainties included: the time and training radiologists need; IT infrastructure and support required; and the trade-offs between sensitivity/specificity performance and the associated costs and worry caused by overdiagnosis. Thus, while the direct costs per analysis from Veye Chest (£5-7.50) would be in the same range as standard NHS scans (£69) and scan reporting (£20) tariffs, the full resource implications could not be estimated [19].

Case Study 2 – prioritising urgent brain scans

In emergency health care and ICU settings, automation based on AI can offer improved speed and alert clinicians to medical images that require prioritization. Aidoc (Tel Aviv, Israel) is an AI-based platform for time-sensitive triaging of patients based on medical images [20]. The solution analyses radiology data directly after scanning and notifies clinicians of any cases with potentially life-threatening abnormalities in real-time, using separate software suites for detecting intracranial haemorrhage (ICH), pulmonary embolism (PE) and large vessel occlusions (LVOs). Aidoc received FDA approval (501(k)) in 2018 for its decision support system as a class II radiological computer-assisted triage and notification software device, and it is also CE-marked.

The CNN-based software continuously works in the background, with optional integration into radiology PACs or RIS, or direct communication to other centres (e.g. to stroke specialist teams). The cost of the Aidoc head suite for detecting intracranial haemorrhages and LVOs ranges between £25,000 and £60,000 per year depending on the requirements and number of exams performed. A 2020 NICE briefing listed Aidoc and four competing AI technologies that offered equivalent triage or diagnostic support based on CT brain scan analysis, with roughly comparable costs [21].

To date the evaluative evidence published included:

- A 2021 published study evaluating performance on 5,585 NCCT head scans (from 6 US sites) that had been reported to be negative for ICH [22]. Of these 25 cases were identified as positive, and following review by three neuroradiologists, 16 were confirmed as ICH. This study demonstrates the potential to reduce false-negative cases, but does not address other aspects of performance.

- A more complete Aidoc validation study published as a conference proceeding was based on 7,112 NCCT head scans from two trauma centres in the US [23]. An accuracy of 98%, sensitivity of 95% and specificity of 98% were reported for detecting ICH.
- Whilst these studies are both retrospective and susceptible to selection bias, a more recent prospective study involved 51,793 head scans from two imaging sites in the US. The study aimed to assess whether the use of Aidoc helped move patients more quickly out of the emergency department or reduced scan turnaround time, by comparing clinical performance pre- and post-Aidoc adoption [24]. The study reported a significant reduction in turnaround time from 53 minutes to 46 minutes for ICH-positive head CT cases and a significant reduction in emergency department length of stay from 567 minutes to 508 minutes (both P<0.001).

3. Pathology

Analysis of removed tissue and biopsies with light microscopy serves a key role in final diagnostic and treatment decisions. However, this creates large analysis workload and in many countries, including the United Kingdom, United States, Canada and Japan, there is a growing shortage of pathologists [25].

Digital pathology - in which stained tissue on glass slides is imaged and reviewed by pathologists on screen rather than using microscopes - has allowed the accumulation of large datasets of slides, which opens the way to training, testing and use of robust deep learning algorithms.

However, the quality of pathology slide preparation – including all steps, from embedding, slicing, staining and scanning – affects the performance of AI in pathology. Variables, such as different brightness levels, the presence of air bubbles and folds or damage to tissue can all affect prediction accuracy, or generalizability of models.

With the recent advances in deep learning, specifically in image recognition, and workload pressure, pathology has become a strong field for applications [26].

A survey of 487 pathologists across 54 countries stated that 75% of respondents were interested or excited about the prospects of AI being used in the pathology workflow [27]. However, uptake may be slowed by the pace of digitisation globally. In the UK, many institutions do not yet involve digitization in the pathology workflow [27].

Case Study 3: Lymph node metastasis - AI technology in development

The CAMELYON16 open challenge aimed at evaluating techniques for the automatic detection of cancer metastasis in sentinel lymph node biopsies from patients with breast cancer. Currently, this requires a large amount of time from pathologists, and there is scope for AI-based automation to reduce pathologist workload and increase detection accuracy.

The open-source dataset contains 400 whole-slide images from Radbound UMC and UMC Utrecht. The winning team from MIT and Harvard Medical School used 256 x 256-pixel patches from positive and negative areas of the whole-slide images to train different classification models with four alternative Neural Network architectures. Their best results gave a final accuracy of 98.4% and an AUC value of 0.925. An independent review of the images by an experienced pathologist had an AUC of 0.966 and combining their Neural Network with the pathologist’s diagnoses significantly increased the AUC to 0.995, representing a 52% reduction in the human error rate.

Challenges such as CAMELYON16 and CAMELYON17, have allowed high-quality open-source datasets to be produced and the acceleration of model development, but none of the algorithms developed in these challenges have progressed to market yet [28][29][30].

Case Study 4: Breast and prostate cancer - CE-marked product

Ibex Medical Analytics created the recently CE-marked Galen platform, an AI-enabled cancer detection system for breast and prostate cancer [31]. Users of the platform have reported a 27% reduction in the time taken to make a diagnosis compared with the standard manual microscope approach, meaning a significant improvement in diagnostic efficiency. Additionally, the total turnaround time has been reduced by 1-2 days, with a 37% improvement in productivity [31].

In common with other computer-aided diagnosis systems (CAD), it can be used for a first-read or second read. In 'First Read' mode, an AI algorithm analyses slides before the pathologist, and highlights areas of interest/concern or prioritises slides; in 'Second Read' mode the platform alerts pathologists when it detects discrepancies between their diagnosis and the AI algorithm's findings, providing a safety net against error or misdiagnosis. As well as detection, the platform also supports pathologists in accurately grading cancers and detecting features including tumour size and invasiveness.

Future uses of AI in pathology

The limited number of pathology AI platforms available currently focus on specific tasks, such as distinguishing cancerous and noncancerous tissue and classifying different tissue types.

Current research, combined with increased data volumes and increased scope for integration across genomics, proteomics, clinical records, and pathology slides is expected to lead to new and wider uses [30]. Future AI is likely to offer:

- The ability to interpret a wider range of pathology samples and extract more information from them, and in addition assess slides with specialised (e.g. antibody-based) markers as well as traditional histochemical stains. As an example of the opportunities, a recent (2021) paper by Lu et al [32] showed that using routine pathology slides alone, deep learning could be used to distinguish primary from secondary (metastatic) cancers and predict the original location of secondaries of unknown origin.
- The ability to integrate multiple data sources with conventional pathology data. For example, Mobadersany et al [33] used a CNN model incorporating histological and genomic data to predict the survival of patients with brain tumours. The new, integrated, genomic and pathology model demonstrated a significantly increased median Harrell's c-index[2] of 0.801 compared with 0.774 achieved using the standard WHO model.

[2] The median Harrell's c-index measures concordance between predicted risks and actual survival.

4. Decision support systems

Using AI to support decisions on which course of action to take presents different challenges to typical diagnostic uses.

In complex healthcare settings, the right decisions usually consider different types of information (the diagnosis and prognosis, the patient's age, general health, treatment guidelines, cost and risk). The data on what constitute the "optimal" decision in a given situation may be patchy or poorly codified, and the right course of action may not be a single act, but rather a complex sequence to be followed.

Nevertheless, because of this complexity, decision support is an important area of opportunity for AI, especially:

- Where there is a vast volume of published information on established best practice that ought to be taken into account;
- Where correctly weighing up all the factors needs challenging calculations;
- In intense settings (ICU, emergency medicine, some surgery), where the volume and speed of data are too much for a human to process completely.

The first and second case scenarios are exemplified respectively by IBM Watson's use in decision support in cancer treatment, and by the NHS use of Kortical advanced modelling for planning blood supply.

Case Study 5 – IBM Watson

IBM Watson, an AI system focussed on question-answering based on vast knowledge banks, was one of the highest-profile ventures in health decision support in the last decade. First highlighted on the US *Jeopardy* quiz show (2011), it used advanced natural language processing (NLP) to interpret questions and select answers from knowledge banks, and was far superior to search engines in finding the most appropriate answer [34].

In healthcare, it was developed further to use NLP to interpret medical records and recommend diagnoses or treatments based on high-quality medical literature and guidelines. However, it proved difficult to realise the original vision in full. In Watson for Oncology (2015), the concordance between expert panel decisions and AI decisions was strong (90%+) in some settings but weaker in others (<75%).

This reflected in part the limitations of relying on the published medical literature alone, partly challenges in fully extracting all relevant information from research papers, and partly the problem of correctly assessing the medical records. Subsequent applications to other data types – for example in processing vast whole-genome data sets (2016 onwards) - showed more added value [34].

Case Study 6 – Optimising blood bank transport

Another application of AI in supporting clinical decisions and workflow efficiency involves blood bank transport. Kortical has developed an AI-based optimization system that predicts the supply and demand of blood products across all hospitals in England [35]. This serves a significant role in ensuring every hospital has an adequate supply of blood platelets when required, whilst reducing the amount of product wasted, particularly as platelets last up to 7 days. The algorithm also works to improve efficiency in transport, considering the blood types, antigens, collection methods, holidays/weekends and weather.

An ML model was developed based on a training set of data from across England up to 2019, and a historical test set from January to June 2019 [36]. Various features from the time series data are calculated, including the number of specific platelets ordered each day, orders received in advance and bank holiday dates. Numerous ML models were trialled using this data to determine the optimal model for predicting blood product demand, whereby an XGBoost model performed best. An app has been made available for the NHS Blood and Transplant team to visualize the predicted demands and stock levels. Kortical has reported a 54% reduction in the amount of wasted platelets and a 100% reduction in the need for urgent transport over 6 months of use. This technology has strong implications for improving the current blood services across the UK, ensuring patients receive the right blood products when required and reduce wastage [36].

Decision support using reinforcement learning

In intensive care, the complex information available and highly dynamic changes encountered make it an active area for AI-based decision support including Reinforcement Learning (RL). While RL is usually based on learning from successes and failures to create an optimized set of rules (referred to as the 'policy'), healthcare models (unlike AI for Chess and Go) usually learn from past data containing wide ranges of treatment decisions and outcomes (termed "off policy" learning).

A total of 21 papers reporting the use of RL for critical care decision support were published between 2010 and 2019 [37]. These involved papers developing models to support the choice of treatment and treatment combinations, drug dosing levels, timing and frequency of interventions, and choice of personal target levels (e.g. target blood glucose level).

A good number of the published studies reported models offering significant improvements on the previously achieved patient outcomes – for example, improving 90-day survival by 4 or 5% - showing strong proof of concept for use of AI in intensive care. However, to date, all the published work has used retrospective data, and prospective validations have not yet emerged. Furthermore, no RL-based alert system for guiding treatment decisions has been approved for use in the healthcare environment yet.

Out of these 21 papers, 15 used the same data source (Medical Information Mart for Intensive Care (MIMIC) II or III) to develop and evaluate their models, and only a few used a separate independent data source for validation. Whilst the MIMIC datasets are of high quality and include data from tens of thousands of patients, this suggests obvious questions about generalisability – but also shows how the creation of a high-quality data source can energise a research field.

Case Study 7 – Sepsis treatment in Intensive Care

At Imperial College London, the AI Clinician project aims to develop reinforcement learning (RL) models for the management of patients in ICU [38]. Previously, the project has published on the use of RL models for the management of intravenous fluids and vasopressors for patients with sepsis in intensive care. Current sepsis treatment strategies are highly variable, whereby there is an opportunity to improve patient outcomes through the optimization of clinical decisions in real-time. The AI Clinician model for optimising sepsis treatment was developed using the MIMIC-III dataset (n=17,083 patients) and tested on the eICU Research Institute Database (eRI) dataset (n=79,073 patients).

A total of 48 features were extracted from both datasets, including demographics, Elixhauser premorbid status, vital signs, laboratory test results, fluids and vasopressors received. Four-hour time intervals were used to create multidimensional time-series datasets, with the optimal treatment strategies given as an output. The model was optimized to improve patient survival 90 days following ICU admission. A total of 80% of the MIMIC-III dataset was used for training, and the remaining 20% was used for validation and selection of the optimal model.

The lowest mortality rates were observed in patients who received similar doses recommended by the AI Clinician. Furthermore, administration of differing amounts of fluids or vasopressors compared with the AI Clinician recommendations was associated with increased mortality rates in a dose-dependent manner [38].

With NHSX AI funding, the AI Clinician is now being further developed and will undergo prospective validation across four ICU departments in different NHS Trusts. The next phase of development will also include work on the quality of recommendations and explanations for clinicians, and integration in current NHS systems.

5. AI for use by the public, patients and carers

As general digital technology becomes more pervasive, powerful and cheaper, and as digital literacy grows, the opportunities for digital health technologies – with or without AI – widen. Applications include:

- Monitoring the well-being of healthy people or patients, or their environment, to improve support and treatment of conditions
- Improving the timeliness and quality of communication with health services, carers and families
- Enabling self-care by providing better information, behavioural feedback and tailored advice

Artificial intelligence has the potential to enhance digital health care in each of these areas, for example:

- Simplifying noisy/long-term data– such as activity or heart rate data – to identify trends
- Creating new insights from routine data – for example, simple wrist-worn motion detectors can be used to provide improved markers for clinical monitoring of disease progression
- Enabling better communication with patients using chatbots to gather more information and/or provide advice/reminders for low-risk or routine issues
- Recognising unusual situations - such as falls – and provide alerts
- Analysing individual/environmental variation and provide personalised advice or nudges

In the UK and internationally, the use of AI to reduce costs or improve quality of care for the growing older populations with disability, long-term conditions, or dementia, is a major focus. Some care organisations began using simple systems – for example, to detect falls at home – over five years ago. The NHSX AI lab is currently working with technology companies on remote monitoring and predictive risk analysis systems to improve adult social care [39].

Specific health conditions and disabilities

As well as digital health applications intended for broad usage, AI is also used in products for people with specific conditions and disabilities. For example, for blind and partially sighted people, the TapTap See app, first launched in 2014, uses image recognition AI to help identify objects, scenes and people, as well as read text [40]. A range of other image-based products is now available, including AI to help with travel, navigating inside large buildings and more recently real-time sign language translation.

General health promotion

Most AI-based products aiming at general improvements in public health – most of which are not regulated medical devices - are based on Apps run on smartphones, wearable fitness trackers, or home computers/ tablet devices. This offers exceptional population reach at very low additional cost, as currently in the UK about 88% of the population have a smartphone and 40% have a fitness tracker of some sort. However the benefits depend heavily on how the target population uses these devices in real life, and a lot of technology is only used sporadically.

Nevertheless, there is growing evidence that low-cost wearables can make some positive contributions. Between 2015 and 2019, 28 studies (mostly interventions of 2-3 months) evaluating whether devices that monitor and feedback on physical activity improve physical activity levels, found there was a consistent small-to-moderate positive effect (equivalent to 1850 extra steps per day), but more sophisticated interventions including personalization features or text messages tended to be more effective [41]. This is consistent with other studies assessing the use of fitness trackers to promote physical activity [42][43].

Personalising Apps to support health goals

Noom is a psychology-based digital health app founded in New York, one of the earlier and better-evidenced health tools, widely used for weight loss diabetes prevention and recognised as a platform for delivering the US CDC's diabetes programme [44]. It uses AI to provide personalised nutrition and exercise coaching based on food and exercise logs from the user, and to support communication, but maintains a 'human in the loop'. Noom has over 25 peer-reviewed publications on the effectiveness of their app for weight loss and diabetes prevention, including a large study on 35,921 obese or overweight users, with 77.9% reporting weight loss over 2 years [45].

Alongside Noom, there is a widening range of apps providing a mix of uniform and personalised advice, providing support for general activity, specific exercises, diet, and weight loss, using AI and non-AI methods. One NHS-approved app, EXi offers personalised tailoring for several different health problems and goals, and is currently included in the NHS app library [46][47].

Other apps, such as Livongo aim to support people with chronic illnesses, including diabetes, hypertension, and obesity to improve their condition [48]. Livongo (part of Teladoc Health) is an AI-based app that supports users in managing chronic conditions and supports multiple devices, including Livongo blood glucose meters, blood pressure cuffs, and digital scales. As users can track their blood glucose and pressure from home regularly, they gain personalised insights into their health.

One study using Livongo's blood glucose monitoring system, identified several predictors of hypoglycaemic or hyperglycaemic events [49]. The study was performed on 7,633 participants, and both gaps between checking readings and an increased number of 'missed medication' tags were associated with inpatient/emergency care visits due to hypoglycaemic events. Livongo's system also found that integrating wider data types, including time of day, medication use and meal tags, improved predictions for individuals at risk of requiring costly interventions, compared to using blood glucose data alone.

Conversational AI

Conversational AI is widely used in business services, and increasingly in healthcare, to automate dialogue with a patient/customer. In health, they have been used to capture basic information and triage patients, and support treatment programmes, medical training, screening programmes, and mental health services. By 2020, there were 31 published studies on chatbots and voice-response agents, with most showing good performance on usability, and effectiveness assessments were either positive or mixed in three-quarters of the studies (23/30) [50]. The field is fast-moving, and most of the published work only reflects early-stage research on aspects such as usability, satisfaction, effectiveness and sometimes privacy, in small scale studies. Of the studies published by 2020, slightly more than half were based on text-based chat only, and 45% had some audio or speech element.

There is extensive AI research into systems that can draw on speech tone and pattern, eye movement, gesture, facial expressions etc., to assess and respond to user's general emotional state, short term reactions (happiness, frustration, attention) within conversations, offering much more sophistication in future products.

Care support for older people and people with dementia

Providing preventive interventions to the aged population to improve health outcomes has become a major area of research and development [51].

Internationally, some public and private care home/home-care systems use AI – and experience to date supports its potential. However, there is a need to ensure the system works in ways that suit older people, professional carers and informal carers, to improve quality of life. For example, monitoring systems can easily lead to alert fatigue without improving care, and some older people have been found to change their daily behaviour to avoid situations that trigger false alerts and inconvenience their family or carers [51].

Most examples of AI-enabled care technology implementation or evaluation in the UK are on a small or medium-scale (<600 homes) at present and include:

- Age UK Medway has teamed up with MiiCare, a digital health company that provides assistive technology for older persons enabling them to stay in their homes for longer, and reduce stress in older people and their families [52][53]. The system includes wearable smartwatches for sleep and physical activity monitoring, an infrared thermometer, pulse oximeter and motion sensors. The digital hub also connects to smart mugs and medicine sensors to keep track of hydration and whether medicines have been taken on time. All the data is integrated and can be shared with family whilst Monica, the voice assistant, prompts users with advice and reminders. A 3-month pilot is currently ongoing on 100 older people in the Medway towns.
- The UK Dementia Research Institute's (DRI) Care Research and Technology Centre has programmes to develop systems - based on affordable technologies for dementia-friendly smart homes, including sleep monitors, conversational agents, vital sign monitoring and robotics. The use of AI could, for example, allow earlier action on urinary tract infections (UTIs). UTIs can lead to hospitalisation and deterioration of a patient's cognitive abilities, but biological diagnostics methods are often used only after the UTI has been present for some time. Research published in 2020 showed the potential for data from passive infra-red sensors, smart plugs, door sensors and sleep patterns to identify probable UTIs, and prompt testing or intervention [54]. AI could also be used to identify falls, spills and other obstacles that could present risks, and conversational agents could be used to provide effective alerts.

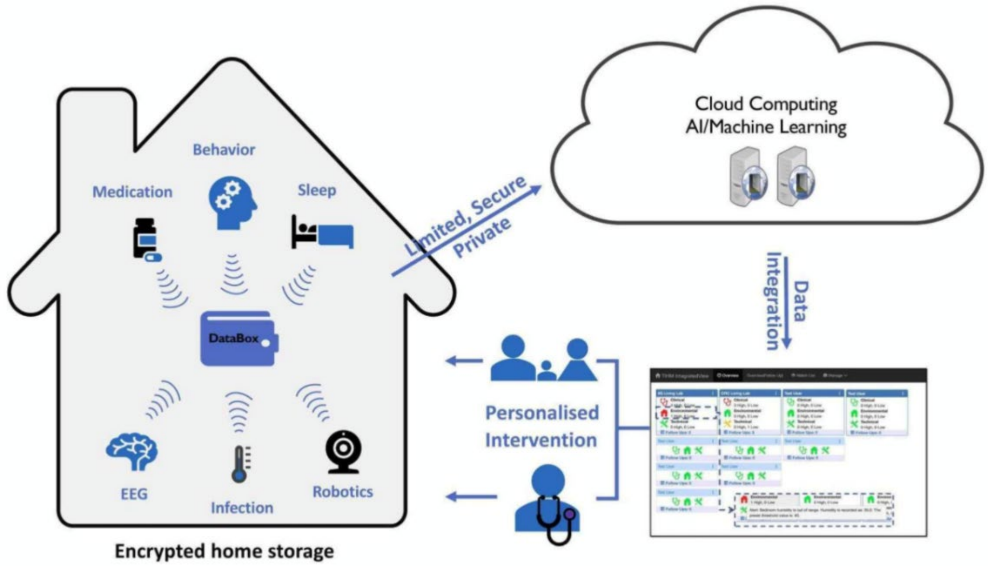

Fig. 2: Diagrammatic representation of the DRI smart home project [55].

Mental health applications

Mental health services in the UK already make extensive use of online care and some digital technologies as part of the long-term programme to Increase Access to Psychological Therapies (IAPT). Apps providing support for general emotional wellbeing, anxiety and mental good health, account for ~30% of the products in the NHS App Library, and a NICE assessment of 14 digitally-enabled therapy programmes (online and mobile apps, mainly Class 1 devices or unregistered) from 2020 can be found here [56].

The large increase in demand for mental health support and management has resulted in a growing number of apps available each year, with currently ~3,857 apps to choose from.

The Organisation for the Review of Care and Health Applications (ORHCA) evaluate digital healthcare apps – based on current standards, regulations and good practice, data security, professional assurance and accessibility – to guide improvements and inform use in health care organizations. ORCHA reviewed 676 mental health-based apps, with only 32% of apps meeting their minimum quality criteria [57]. Among the more specialised apps, 52% of addiction-management, 45% of CBT apps, and 44% of self-harm management apps met the minimum ORCHA criteria [57][58].

Case study 9 – Gaming-based ADHD treatment

A lot of current use of AI in mental health applications involves use of NLP-based conversational agents to improve the provision of psychological support. But newer approaches include EndeavorRx, and FDA approved ADHD treatment delivered as an AI-enhanced video game (2020), and ongoing research is exploring opportunities, such as indicators of depression in social media platforms, voice logs and messaging services; personalisation of digital therapies; and integrating biomedical data (e.g. genetics, neuroimaging) with clinical data and everyday data sources [59].

EndeavourRx has published several clinical validation studies, including a 2020 randomised, double-blind, parallel-group, controlled trial on 348 children with ADHD [60]. The study reported that the EndeavorRx platform significantly improved performance on an objective measure of attention, Test of Variables of Attention (TOVA), in patients with ADHD compared with the digital control intervention over 4 weeks. A more recent publication on 206 children with ADHD, reported that 68% of parents observed an improvement in their child's ADHD-related impairments over 3 months (2 months treatment with 1-month break in between) followed with no serious adverse events [61].

Case study 10 – mental health platforms

The NHSX programme funding announced in 2021 included its first evaluation of the psychiatric intervention, Wysa. Wysa is a Class I device, providing an AI-based chatbot that uses evidence-based cognitive behavioural therapy practices. The new study will evaluate the performance in reducing symptoms of anxiety and depression for patients on the waiting list for regular treatment, and in detecting people in need of priority treatment [62].

Ieso Digital Health is an online platform that provides cognitive behavioural therapy through over 70 NHS Trusts [63]. Patients are paired with therapists for virtual appointments and can track their progress through questionnaires. Ieso is currently partnered with and is fully adherent to NICE guidelines. The company's use of AI focused on the analysis of patient language and interactions in therapy sessions – and the models developed are then used to support their online therapists with diagnoses, advice on predictors of successes or failures, and how to maximise treatment effectiveness.

6. Concluding remarks

This is not a comprehensive list of AI-based applications in healthcare – we have aimed to give illustrations that show the diversity of AI applications in healthcare, and the types of AI that have been approved for use or large clinical trials to date. In the space available, we have not been able to include every area – for example, we have not discussed AI systems in guiding surgery and radiotherapy, or applications in ECG analysis.

Nevertheless, we hope that this short overview of the state of progress by 2020 provides a useful background for discussing the ever-increasing range of AI applications emerging from research in the UK and worldwide.

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