ELEC0139
Final Blog Submission

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Abstract

This report contains the PDF version of the final blog. It is verified that the total word count of the blog is 4772 Words. The online version hosted on a website can be seen by clicking HERE or using this link : https://ucl-elec0139-blog.netlify.app . The online blog consists of 4 posts and this report version is divided into 3 parts as mentioned in the moodle guide.

Part 1 of the Blog

Evolution of AI from Theory to Reality

In the 1950s, Alan Turing had posed his famous question "Can Machines Think ?". Back then, he considered the question to be vague & ambiguous and instead proposed the Turing Test as a way to measure the intelligence of machines [1]. It had human evaluators judge conversation transcripts between a machine and a human and identify which was the machine. Seven decades later, we are closer than ever to hitting this benchmark with the latest large language models (LLMs) like GPT o4, Deepseek R1 easily passing the Turing Test [2]. They are capable of complex thought & reasoning, fluent dialogue, and even image generation. AI/ML models have been theorized for and even implemented such as the M.P. neuron or the Perceptron for over half a century. From these theoretical concepts, it has evolved massively with the potential to be embedded in all aspects of modern life as seen below.

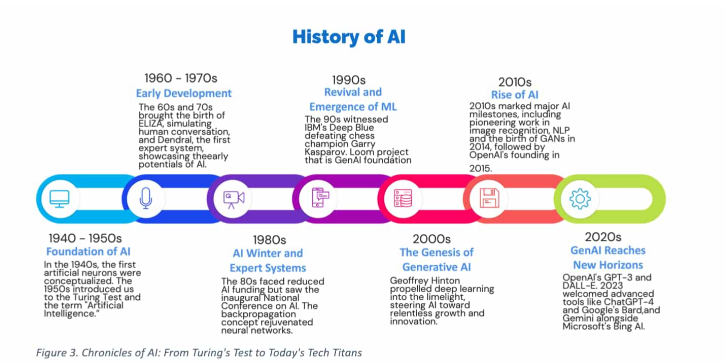

Figure 1: History of AI

While its capabilities are real and growing, so is the hype surrounding it with many arguing that we are currently in an AI bubble where companies are adding AI features that weren't even asked for such as smart AI enabled toothbrushes or another AI startup whose entire business model is just a wrapper around ChatGPT. But while gimmicky AI products dominate headlines, the healthcare sector shows where AI might actually be revolutionary, benefitting significantly from recent advancements in AI.

The Global Healthcare Crisis

Currently, healthcare systems around the world are in unprecedented strain due to multiple challenges. One of the main issues is the growing gap between patient demand and availability of medical facilities. The World Health Organisation (WHO) estimates a shortage of 10 million health sector workers by 2030, with it disproportionately affecting low and middle income countries [3] (as seen in this map below made by the WHO). Even in developed countries like the UK, the National Health Service (NHS) is currently facing a record backlog with millions of patients still awaiting treatment with delays in surgery, appointments and even diagnostics [4] as seen in this graph.

Figure 2: NHS Backlog

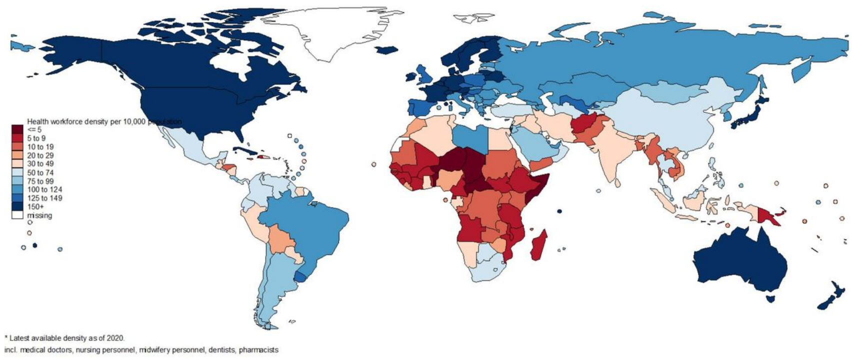

Figure 3: WHO map showing current density of healthcare workers

The issue is made even worse due to aging populations in developed countries and negative population growth (as seen in this figure of Italy's pop. pyramid), growth in life expectancy has led to issues like diabetes, cancer and heart disease more common. The demographic issues put extra pressure on a system that's already stretched thin. Healthcare worker burnout has reached critical levels made worse by the Covid-19 pandemic [5]. Studies have shown that higher levels of stress & fatigue among medical workers have caused lower productivity and increased medical errors.

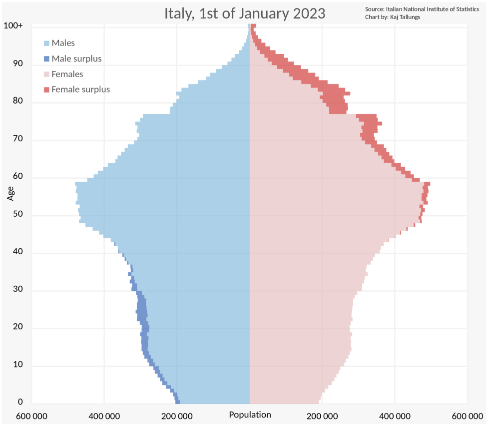

Figure 4: Population Pyramid of Italy (2023)

Another major issue facing the sector is inefficiencies in the healthcare delivery process. Manual documentation and using outdated systems often lead to poor coordination leading to misdiagnosis and delayed treatment. Studies have shown that this affects 1 in 20 patients in the USA, a figure that is extremely high when considering the exorbitant costs of healthcare in the country [6]. Access to healthcare is also another issue. Rural areas often suffer from limited access to specialist staff, testing equipment, or even having no hospitals itself. Medical problems deemed less important like mental health services are usually underfunded and understaffed in such rural areas [7].

How AI/ML can Increase Accuracy/Efficiency and Improve Access

AI and ML techniques can offer a viable and much needed augmentation to the entire domain. Advancements in computer vision and deep learning have created previously unimaginable diagnostic capabilities. Studies have shown that AI based systems utilizing computer vision can match or even outperform expert radiologists in tasks like detecting pneumonia from chest X-rays or even identifying early signs of cardiovascular disease. DeepMind by Google developed an AI model that outperformed human specialists in breast cancer detection from mammograms. There are already startups like Viz.ai and Aidoc [8], that help hospitals integrate AI image analysis tools into their workflow. Furthermore, AI systems can also analyze patient records and real-time health data to create personal treatment plans unique to each patient. It has the potential to dramatically expand access to healthcare in lower resource regions of the world, supporting healthcare workers by automating triage and reducing burden on the already overworked staff.

Figure 5: Futuristic AI integration in pediatric healthcare

AI chatbots and virtual assistants have already been deployed by the NHS (North West London NHS Trust) during the Covid-19 global pandemic which is a real example of AI expanding access to healthcare and reducing the burden on healthcare staff. The chatbots were available 24/7, offer basic advice regarding symptoms, triage non-emergency queries and even followed up previous messages like a human conversation. This automation helped reduce the burden on clinical staff and freed up doctors to focus on more complex cases [9]. Early preventative care is another area where AI shows significant potential. ML models can identify patients at risk well in advance of traditional screening methods by analysing data such as lifestyle choices, genetic data and health records. By having earlier interventions, such systems can reduce hospital visits which lowers healthcare costs and can save lives. The integration of AI with wearable health devices like fitness trackers, is further reshaping the healthcare landscape. They allow patients to monitor various vital health metrics themselves without needing to visit clinics.

However, the integration of AI into healthcare comes with its own issues regarding bias, ethical concerns, lack of transparency, and questions of accountability. Thus, it is essential that fairness, trust and safety are prioritized considering healthcare is a field where accuracy and speed could be the difference between recovery and death. The next section of the blog will cover how different AI/ML technologies address the aforementioned challenges in the healthcare domain in much more detail and is complemented with a brief description of such ML/AI technologies.

Part 2 of the Blog

While the previous section talked about the current state of the healthcare domain and made the case for adopting AI/ML tools, it's just as important to understand the actual technology behind it and look beyond just the hype. Different tools solve different problems, from reading scans to predicting diseases. This section explores five key AI/ML tools, how they work and how they are already making a difference and solving challenges in the sector.

Computer Vision

Computer Vision is the sub-branch of AI that deals with computers being able to analyse images and it is revolutionizing medical imaging. Instead of just analyzing singular pixels as is done in a basic neural network (ANN), computer vision models are able to recognize patterns and features like shadowy nodules in the lungs which could be a sign of cancer, just like an experienced radiologist can. These models are experts at detecting subtle patterns that even most humans might overlook and are both consistent and fast at it. They typically use Convolutional Neural Networks (CNN) [10] which uses multiple filters in 2D-Conv layers where the filters are passed over the input image to detect patterns like edges or shapes. Early layers might pick up simple features while the later layers use that information to capture more complex features like tumors in lung scans. These filter values get fine tuned during the training stage while thousands of labeled images are used to get the model to learn and identify relevant features in them. Such CNN based tools can act as a second pair of eyes passing on any information they get to the healthcare staff.

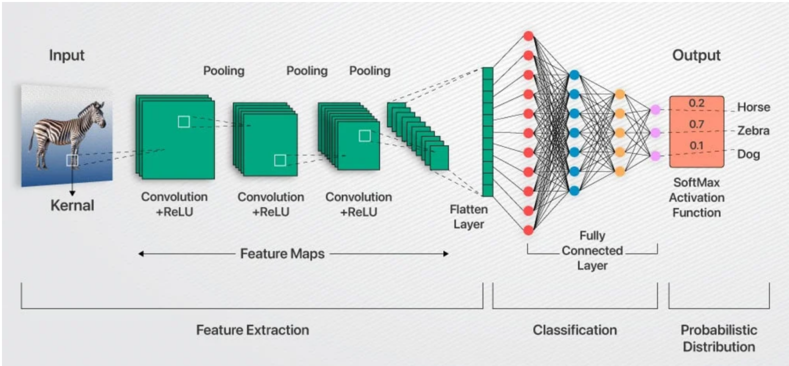

Figure 6: CNN Architecture

Computer vision is tackling numerous healthcare challenges, it can identify abnormalities in radiology images like CT scans, MRIs, and X-rays or assist in pathology by scanning slides for cancer cells. In eye care, AI systems can be used to analyze retinal scans and check for diabetic retinopathy early. In dermatology, they can check photos of skin lesions for melanoma risk. The main goal is to reduce the heavy workload of specialists and improve accuracy as well. As seen in the previous section, AI tools have been able to outperform even expert radiologists when it comes to tasks like detecting pneumonia from chest X-rays or even identifying early signs of cardiovascular disease. Health centres can also integrate AI tools to prioritize urgent cases so that patients who need urgent care from specialists can get it in time.

The NHS has already started deploying such tools at scale. In 2023, NHS England created an AI Diagnostic Fund to adopt approved AI models. An AI system by Annalise.ai that can detect 124 different findings on chest X-rays from lung nodules to misplaced medical tubes is being rolled out to over 40 NHS trusts [11]. At NHS Grampian in Scotland, UK where it was tested; the AI cut the time from X-ray to lung cancer treatment by an average of 9 days. Such gains can be life-saving, given how important starting treatment early is for diseases like cancer. Another example is breast cancer screening where in a 2023 NHS trial of 10,000 mammograms [12], An AI system developed by Kheiron Medical found early signs of breast cancer in 11 women that human doctors had missed. These cancers were near impossible to detect using the human eye yet the AI was able to do it. The goal is that by integrating computer vision models into screening programs, cancers and other diseases can be caught at an earlier stage [13]. In all these cases, the AI only suggests its prediction but the final decision is made by the healthcare workers which makes Liability interesting if something goes wrong, more about this will be explained in the next section. When used responsibly, computer vision in healthcare is a powerful helper, reducing workloads and potentially saving lives too.

Natural Language Processing (NLP)

NLP is the sub branch of AI that allows computers to understand human language and emotions/meanings from text. They use models like Transformers (which is what is used in LLMs like ChatGPT) to parse through the given text [14]. A large amount of medical information exists in text form such as doctors prescriptions, nurses reports or lab test data. NLP models can read them and extract useful information from it or even generate new text from it. By training these models on a vast amount of medical data, they are able to learn medical terminology and understand all the abbreviations and complex terms. It can even capture context from sentences so for example if a sentence contains "Jaguar", the program can understand if it's talking about the animal or car company. NLP can drastically reduce burdens on administrative tasks by automating them, they can be used to listen to conversations with patients and generate notes or letters as needed. It can be used to parse through patient records and extract any useful information from them instead of having staff manually go through each record. NLP can power chatbots which can answer patient questions and have full conversations with them, or even help them book appointments [15].

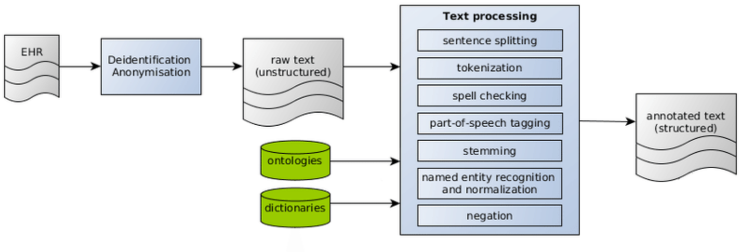

Figure 7: NLP Pipeline for processing Health Records

The NHS has also trialed NLP models such as an AI assistant called TORTUS. In 2024, Great Ormond Street Hospital led a London-wide pilot with 5,000 patients to test whether an NLP system could streamline documentation [16]. The TORTUS system uses speech recognition and a generative AI backend to listen to clinical consultations and draft the outpatient letters and notes automatically. Doctors would then review and edit the drafts before finalizing the document. The main aim was to reduce time doctors spent in front of the computer screen and let them focus more on patients. Early results were positive and doctors reported that it can significantly reduce time spent on writing letters, potentially increasing face-to-face time with patients. Dr. Dominic Pimenta, TORTUS's developer, noted that this kind of AI tech could "massively improve healthcare workers' lives" and relieve pressures if proven safe and effective.

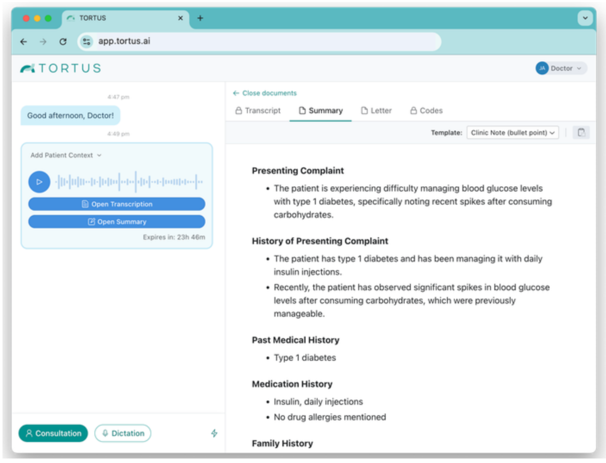

Figure 8: TORTUS Assistant

Beyond documentation, NLP is also helping make medical information more accessible. Researchers have explored using large language models like GPT-4 to simplify medical jargon in clinic letters into plain English for patients. This could bridge communication gaps, ensuring patients understand their care better. Moreover, chatbot-based symptom checkers which some NHS services have already experimented with in triage settings use NLP to interpret a patient's text descriptions of symptoms and asks follow up questions, mimicking a nurse's triage process [17]. While such chatbots must be used cautiously, they show how conversational AI can improve healthcare. The key with NLP in healthcare is maintaining accuracy and empathy as the AI must not misinterpret critical details or generate incorrect info which could lead to disastrous consequences.

Generative AI

This is the sub branch of AI that consists of models that create new data such as images, text or time series data by learning patterns in the existing training datasets. Instead of just analysing the training data, they try to generate synthetic data that resembles it. Some common types of models used for this are Generative Adversarial Networks (GANs), Variational AutoEncoders (VAEs) and Large Language Models (LLMs) [18]. GANs consist of two parts, the generator and the discriminator. The generator produces synthetic data while the discriminator tries to check if the data is real or fake (synthetic). Through training, the generator gets better at producing data close to the real training samples. CycleGAN is a special type of GAN that actually contains two GANs which work in tandem. This setup allows it to be used for tasks like image translation from one domain to another like converting MRI scan images to CT scan images, and this can be done without needing paired training data.

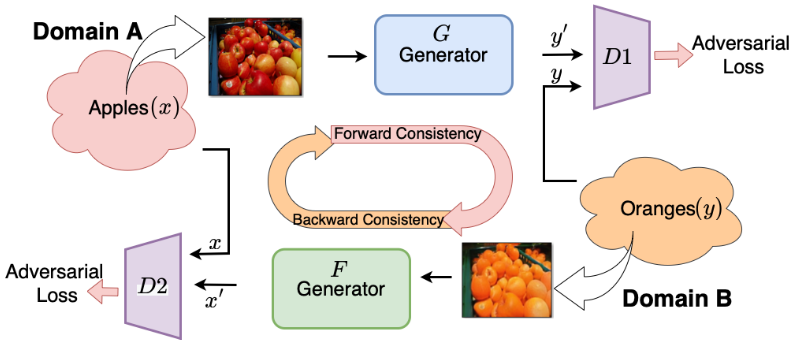

Figure 9: CycleGAN Architecture for Image Domain Translation

With reference to the healthcare domain, generative AI is currently being used in imaging, documentation, simulation and even drug discovery. In medical imaging, generative AI models are used to augment existing dataset, to add synthetic data for minority classes. They can be used to create synthetic patient health records to safely train and test ML models with any worry about breaching privacy. LLMs can be used to help workers in drafting sick notes or other required documents like discharge summaries. In the pharmaceutical sector, which is related to healthcare, generative models are able to generate novel molecules for drug research. Hospitals are even testing the concept of “digital twins” which are virtual patient simulations to test treatments from actually applying them to the real patient [19]. A real world example of Generative AI in healthcare is seen in the research paper that managed to train a CycleGAN to convert between MRI and CT style brain scan images [20]. Since MRIs show soft tissue well while CTs show bones well, doing both tests is the ideal choice, but patients are often not able to get both due to a multitude of reasons. The AI was trained on unpaired public datasets and learned to generate CT-like images from MRIs. This helped radiologists visualize bone structures without extra tests or radiation exposure. This has high potential in brain tumor analysis and radiotherapy planning. Also, as mentioned above, the TORTUS project in the UK trialed NLP models along with a generative AI backend to automatically draft outpatient letters, cutting documentation time. Such synthetic data must always be validated before use as these outputs are worthless if they are medically inaccurate, Generative AI models like LLMs are also prone to Hallucination where they output clearly wrong facts and thus proper regulations must be in place, more about this will be discussed in the next section.

Remote Monitoring + ML

Wearable as well as remote health monitoring tools are changing how healthcare is considered outside hospitals and clinics. Devices like smartwatches and fitness trackers can track various vital signs like heart rate, blood oxygen, breathing rate, amount of activity and so on continuously [21]. ML tools can be used to extract information from this data, spotting subtle changes in the vital signs that indicate worsening health. Predictive analytics can also be done when the live data is used along with historical data to spot health issues before they become noticeable normally or before it becomes life threatening. Various kinds of ML models can be used for such tasks like basic decision trees, or neural networks or more commonly an ensemble method. Such models allow people to start treatment early instead of waiting for symptoms and then getting it diagnosed. Such Smart devices can even flag more serious diseases like abnormal heart beats or lung issues. Hospitals can even use such tools to track which patients are more likely to end up at the hospital again. The NHS had trialed an app based system called ACE-CF which monitors cystic fibrosis patients [22]. By analysing lung data, the system can flag the possibility of infections upto 10 days earlier.

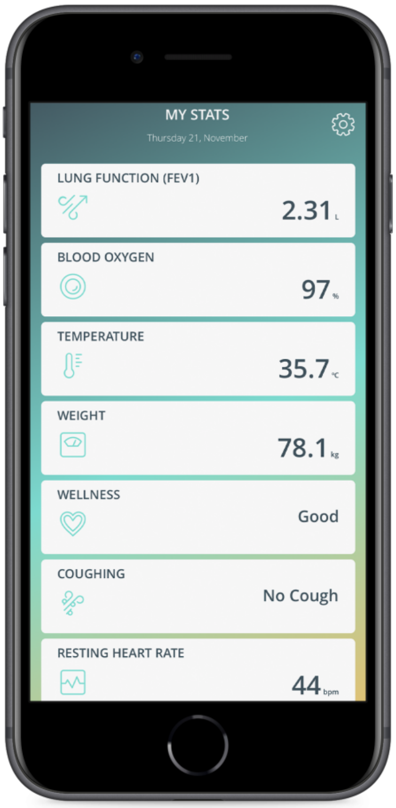

Figure 10: ACE-CF App Dashboard

Another project by Cera looks at home visit records to flag fall risks for older people [23]. The NHS claims that these projects help cut down thousands of avoidable hospital visits daily. UCL , along with King's College London are working with NHS England on a national project called foresight which uses generative AI to make predictions about patients on things like hospitalizations and diagnoses [24]; it is trained using over 50 Million anonymized records. Such systems are obviously not perfect and the predictions can often reflect bias in the training data. The next section will cover the Ethical side of using AI for healthcare in more detail.

Part 3 of the Blog

The previous sections of the blog have shown the effect AI/ML can have on the healthcare domain but while these technologies offer unprecedented capabilities in treatment and diagnostics, they also raise serious ethical, legal and societal issues. Problems like bias, lack of accountability & transparency, data privacy concern cause an overall lack of trust in such AI systems. In the UK, the National Health Service (NHS) has actively tried to integrate AI so as to increase efficiency and clinical outcomes. However, they have encountered multiple issues while doing so which will be described in more detail in this section of the blog as well as the risk if AI systems are left unchecked and what the UK and EU are doing to ensure that such technologies are used fairly and ethically.

Bias & Fairness of AI in Healthcare

One of the main ethical issues in the usage of AI for healthcare is algorithmic bias. Bias happens when an AI model unintentionally favors some groups over others because of imbalances or flaws in the dataset used to train the ML models. In healthcare, such biases can even lead to clinical harm and erode people's trust in the system. A recent example of this was pulse oximeters, which were found to overestimate blood oxygen levels in humans with darker skin tones. Although no AI was involved here, it highlights how even commonly used medical devices can have systemic flaws and biases [25]. Imagine the outcome if similar issues happened in AI systems due to flaws in the data used.

Studies have shown that ML models trained to detect melanoma performed much worse on test subjects with darker skin once again, it was attributed to the underrepresentation of such patients in the training dataset. ML models for chest X-rays and cardiovascular risk have also performed more poorly for minority classes like women and ethnic minorities. These cases are not coincidence, they are caused by using training datasets that disproportionately represent white, male, and affluent patients, this reinforces bias and inequalities in clinical outcomes. Also, when AI models are evaluated only on aggregate accuracy, their underperformance on smaller and underserved classes often goes unnoticed.

Bias can also arise from historical data that reflects disparities in procedure. Studies have shown that black patients in the UK have historically been prescribed less pain medication than white patients for the same conditions, due to racially biased assumptions about black people having a higher pain tolerance. If an AI system is trained on prescription records that reflect these disparities, it may think that certain ethnic groups need less pain medication. In practice, this could lead the model to recommend less aggressive pain treatment for black patients.

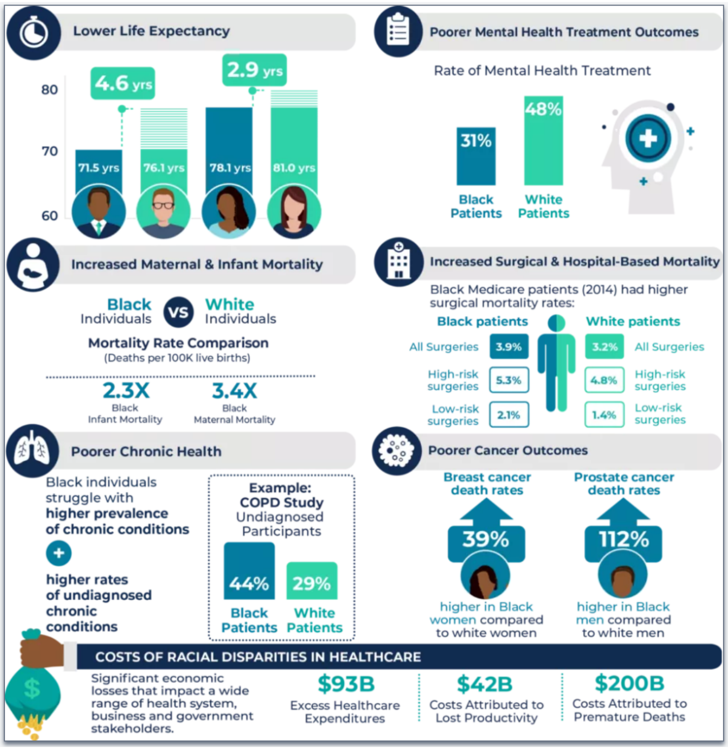

Figure 11: Racial Bias in healthcare in the USA

This creates a positive feedback loop where patients receive less care which is used to train the AI further resulting in future patients receiving even less care because the AI deems from the training data that they don't need as much medication. This is extremely dangerous and is effectively automated systemic discrimination [26]. Some methods can be used to reduce such bias resulting in more fair and equitable AI models such as:

– Diverse data sourcing to reflect real-world demographics.

– Subgroup performance analysis instead of just overall accuracy.

– Fairness-aware model selection, using metrics like equalized odds or demographic parity.

A UK government review found that many medical devices, including AI ones show performance gaps across ethnic and gender lines. It recommended actions to consider fairness at every stage of the AI lifecycle from how data is collected to how systems are monitored after deployment [27]. Bias in Healthcare is not just a matter of ethics, it is a clinical issue which if left unaddressed risks making existing inequalities even worse than it already is.

The Need for Explainability & Trust

A major issue with many AI systems (especially complex deep learning models) is their lack of interpretability. In the case of healthcare, when workers aren't able to interpret the working and understand how the AI model came up with the conclusion it reached. This opacity can cause serious problems, this is known as the Black Box Problem. There are tools for explaining how AI's came to a decision like saliency maps and feature attribution methods which shows what part of an input influenced the models decision. But, these explanations are often misleading or unstable, highlighting areas that affect the output but don't mean anything clinically. This causes healthcare workers to not clearly trust the model's reasoning. Research on trust in explainable AI (XAI) shows mixed results. When the explanations are clear and clinically relevant, they can improve confidence and lead to better diagnosing of patients, but when the explanations are vague/misleading, it can backfire, with workers relying overly on AI to the point that they trust the output, even when it's wrong or not sensible [28]. Development of Interpretable by design AI models can solve this issue, some methods they use are:

- Generalized additive models (GAMs), they weigh individual risk factors in a transparent manner to show how they come to some prediction.
- Rule-based systems, they back up their predictions with if-then logic that healthcare workers can use to verify the results.

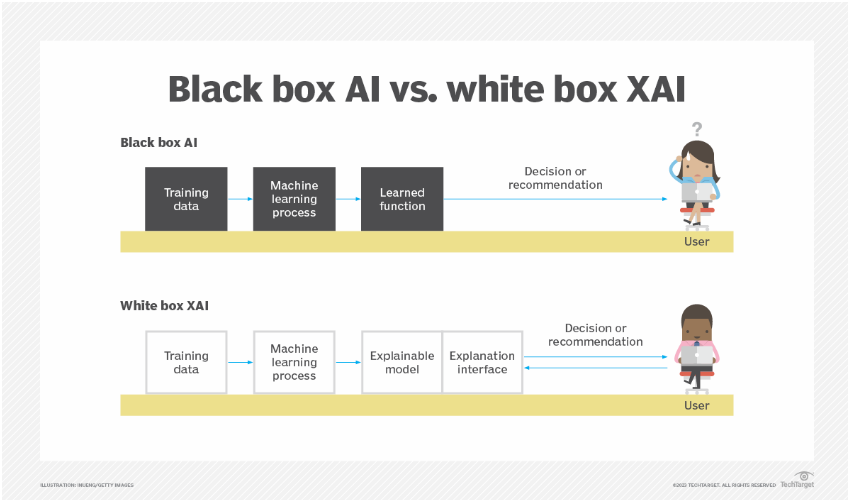

Figure 12: Black box AI vs XAI

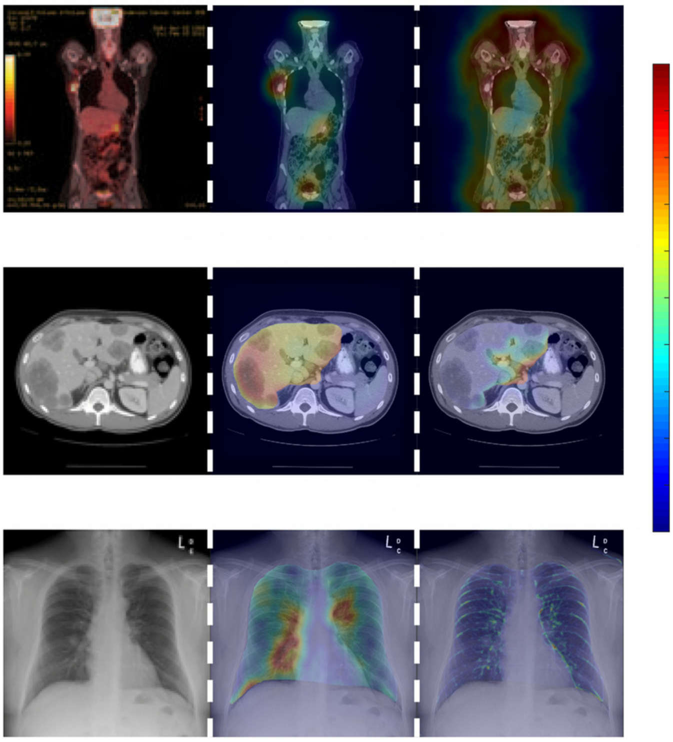

Figure 13: Saliency Maps

Data Privacy, Consent, and Governance

Another major issue is the need of sensitive health data for training Healthcare AI models. Most developed countries have strict privacy regulations regarding medical data like electronic health records (EHRs), genomic data, and diagnostic image results. In the UK, there is the Data Protection Act 2018 which is aligned with the General Data Protection Regulation (GDPR) [29]. AI research faces multiple real world barriers, Patient data is often siloed across multiple NHS trusts making it hard to train robust AI models using all the data. Even if the trusts collaborate, there are still complex approval processes and consent needed to gain access to the patient data. Deidentification techniques are usually used to anonymize the data but studies have shown that it is possible to reidentify over 80% of individuals in anonymized datasets using ML models trained on public data which is a huge privacy breach [30]. Furthermore, some medical data like facial structure in cranial MRI's are impossible to anonymize without losing out vital information. To mitigate these issues, the NHS have used the following privacy preserving methods: - Federated Learning (FL), models are trained using decentralized data sources without actually moving the patient data off-site. - Differential Privacy (DP), adds statistical noise to ML model outputs which prevents reverse engineering of individual records making it harder to reidentify individuals. - Trusted Research Environments (TRE), are secure digital workspaces where researchers can analyze sensitive data without being able to download, copy, or misuse it thus minimizing the risk of data exposure [31].

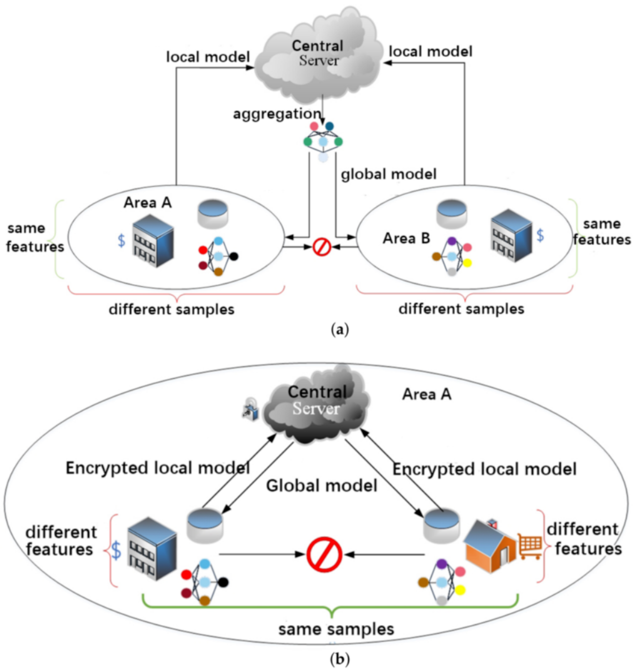

Figure 14: Federated Learning

Legal Accountability and Shared Liability

As AI gets integrated into the medical field, it raises a lot of questions about accountability. If one of these models misdiagnoses a patient or outright suggests the wrong treatment plan, who is liable for it ? Is it the doctor who used the AI tool or the hospital, or the original developer that created said tool. Currently, the UK does not have any AI specific liability ruling, instead general medical rules can be applied. In this case:

- The healthcare worker can be held responsible for over relying on the AI tool
- The developer company can be held for creating software deemed defective.

- The hospital can be held responsible for failure in properly implementing the software without oversight.

But the question of Liability gets messy if we're considering more complex AI systems with autonomy. There are AI systems that make decisions autonomously without any human override or transparency. If such systems misdiagnose, the responsibility will likely fall purely on the developers since the healthcare staff had no role in it. However, if AI systems are only used as a suggestion tool with the hospital staff having the final say in all decisions then the responsibility could be on the person who made the decision entirely [32]. The Medicines and Healthcare products Regulatory Agency (MHRA) maintains that AI tools are only to be used for assistance and that human staff should remain the final decision makers. However, as AI grows more complex, a more detailed framework is needed to determine responsibility in such cases.

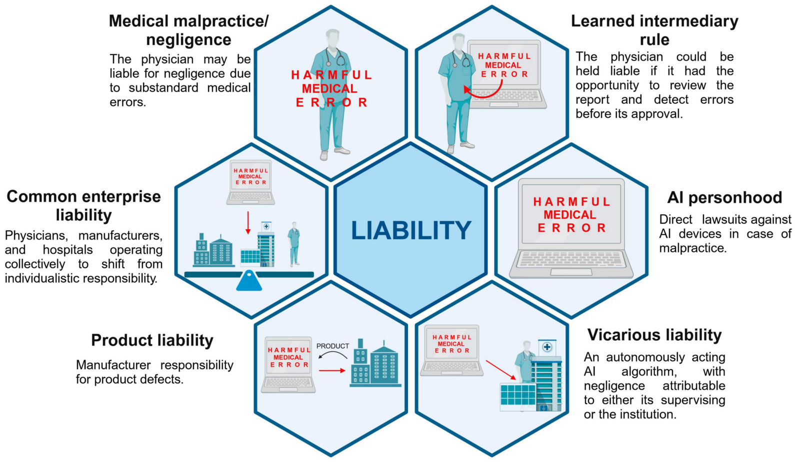

Figure 15: More Examples of Legal Accountability

Regulation: UK and EU Approaches

Regulators in various countries are solving these ethical issues with different strategies. The EU's AI Act, passed in 2023, is the world's most comprehensive framework for high-risk AI applications such as those used in the healthcare domain [33]. The EU AI Act contains sections on mandatory risk assessments, bias mitigation, requirements for human oversight and even mandates on transparency such as disclosing limitations. The UK meanwhile has opted for a more flexible approach to AI regulation. Instead of adopting a standalone AI bill, it has issued regulation white papers and asked existing bodies like the MHRA to adapt their ruling and to consider the role of AI [34]. They have also introduced several practices to support safe and ethical AI such as:

- The AI Airlock Sandbox, which allows for real-world testing of new AI technologies in a safe environment.
- Revised Good Machine Learning Practice (GMLP) guidelines.
- Updated medical device classification rules to reflect the risks posed by AI
- Collaboration with international regulators like Health Canada to equalize AI safety standards

Ultimately, the goal is not just to build intelligent AI systems, we need to also ensure that the systems are operating justly and supporting healthcare delivery in a way that protects everyone including all minorities.

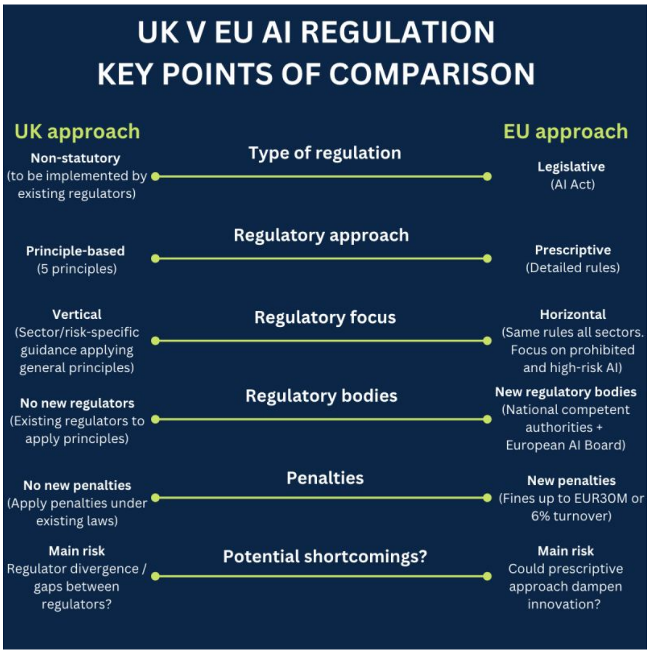

Figure 16: UK vs EU on AI Regulation

Conclusions to the Blog

In this Blog, we have seen the declining state of Healthcare globally and how integration of AI/ML tools into healthcare is not just based on hype but instead provides multiple benefits from reducing staff workloads using computer vision tools for diagnostics, to automating document creation using NLP tools, to generating synthetic data for testing models using generative AI, each technology has has been trialed in the real world with good results. Such tools improve accuracy, expand accessibility and even allow for personalized care plans.

The NHS and similar institutions worldwide are beginning to recognize the utility of AI. Initiatives like the AI Diagnostic Fund and pilot projects such as TORTUS and Foresight are early signals that AI in healthcare is moving from lab prototypes to scalable, deployable solutions. In rural or low-resource areas, AI could bridge critical access gaps, bringing expertise and care to communities that would otherwise receive no treatment. However, the adoption of AI comes with many complications. Ethical concerns regarding bias, fairness, and accountability need to be considered. If these systems are trained on flawed or incomplete datasets, they risk amplifying existing inequalities, especially for already marginalized classes. Similarly, black-box models that cannot explain their decisions reduce trust in AI and raise liability questions when something goes wrong.

The legal and regulatory landscape is moving fast. The EU has taken a structured, detailed approach with the AI Act, while the UK has opted for a more flexible format, leaning on regulatory bodies to adapt existing rules. Regardless of the approach, they have a common goal which is to create systems that are not only intelligent but also fair, transparent, and safe. To conclude, AI in healthcare should only be seen as an human assistant and not a replacement for experienced humans. Its role must be guided by robust oversight, continual evaluation, and above all, empathy for the patients it seeks to serve. When implemented responsibly, AI/ML technologies hold the potential to shift healthcare from reactive treatment to predictive and equitable care. But this can only be achieved if future improvements in performance are also matched by improvements in accountability, bias and fairness. The future of healthcare may be powered by AI algorithms but it must still be decided by people.

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