The potential of Artificial Intelligence (AI) within Public Health and healthcare systems in Scotland

An introductory discussion paper

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Key terms used in this report

These terms are presented in the order in which they appear in the report:

General Purpose Technology (GPT) – A transformative technology with widespread applications across industries, significantly impacting economic and social progress, such as electricity, the internet, or artificial intelligence.

Artificial Intelligence (AI) – The simulation of human intelligence in machines, enabling them to perform tasks such as learning, reasoning, problem-solving, and decision-making.

Algorithmic Bias – Systematic errors in AI decision-making that result from biased training data or flawed algorithms, leading to unfair or discriminatory outcomes.

AI Training Data – The datasets used to teach AI models by exposing them to examples from which they learn patterns, rules, and behaviours.

Natural Language Understanding (NLU) – A subset of AI that enables machines to comprehend and interpret human language, including context, intent, and meaning.

Machine Learning (ML) – A branch of AI that enables systems to learn from data and improve performance over time without explicit programming.

Structured Labelling – A systematic approach to annotating data with predefined categories or attributes, ensuring consistency and accuracy for AI training and analysis.

Generative AI – AI systems that create new content, such as text, images, audio, or code, by learning patterns from large datasets.

Nongenerative AI – AI models that analyse, classify, or make decisions based on existing data without generating new content.

AI Hallucinations – Instances where AI generates false, misleading, or nonsensical information, presenting it as factual.

Data poisoning – In AI software development, it refers to the intentional manipulation or corruption of training data to deceive or degrade the performance of a machine learning model. It is a type of adversarial attack aimed at introducing vulnerabilities or biases during the model's training phase.

Supervised Machine Learning – A machine learning approach where humans guide the training process, ensuring the AI learns with accurate and unbiased data, while acting as a safeguard against errors and biases.

Explainable AI – AI systems (often nongenerative AI) designed to provide transparent and interpretable reasoning behind their decisions, which can be assessed using established statistical approaches, which improves trust and accountability.

Black Box AI – AI systems (mainly generative AI) whose decision-making processes are opaque and difficult to interpret, making it challenging to understand how conclusions are reached.

White Box AI – AI models (mostly nongenerative AI) that are transparent and interpretable, allowing users to understand the logic and factors influencing AI-driven decisions.

Social Big Data – Large-scale data collected from social media, online interactions, and digital platforms, often used for AI-driven insights into human behaviour and trends, including recent forms of public health surveillance.

Sentiment Analysis – An NLU technique that uses AI to determine the emotional tone of text, classifying it as positive, negative, or neutral. It is commonly used in social big data monitoring, customer feedback analysis, and market research.

Federated Learning – A machine learning approach that enables multiple devices or organisations to collaboratively train AI models without sharing raw data, enhancing privacy and security.

AI adoption – The process of integrating AI technologies into business operations, products, or services to enhance efficiency, decision-making, or innovation. It involves organisational readiness, strategy, robust ethical and safety governance and the careful implementation of AI tools within existing or redesigned systems.

AI Revolution – The transformative shift in industries and society driven by AI advancements, reshaping economies, healthcare, education, and labour markets.

AI Creep – The gradual and often unchecked expansion of AI into various aspects of daily life, often lacking coherence and transparency, which can lead to ethical, privacy, and accountability concerns.

Technological Arrogance – The overconfidence in technology's ability to solve complex problems, often overlooking systems and context as well as ethical, social, or unintended consequences.

Technocratic Elitism – The belief that experts and technologists should dominate decision-making, sometimes at the expense of public, democratic or diverse perspectives.

Introduction

A General Purpose Technology, or GPT, is a term used to describe a new method of inventing and producing that can be of such magnitude that its use will have a protracted collective, and even global, impact[1]. The steam engine, electricity and Information Technology are often cited as impactful forms of GPT[2]. Predicting the societal impacts of GPTs and their uses (and misuses) has been proven to be fraught with difficulty, or even impossible[2].

More recent forms of GPT include the internet and social media[3]. Few foresaw the internet's profound and all-encompassing impact on humanity, transforming how we communicate, work, learn, and even think. What began as a niche technological experiment, to share files among government researchers in the 1980s, has become a global force reshaping economies, politics, and cultures on an unprecedented scale, connecting billions of people and redefining every aspect of modern life[4].

Similarly, when Six Degrees, one of the first major social media platforms, was established in 1997, it was unclear how later evolutions of social media would become such powerful worldwide phenomena, influencing everything from personal relationships to politics, business, and culture, with billions of users engaging every day, across various platforms[5, 6]. TikTok, for example, has been shown to influence the outcomes of political elections globally, not least, through its incredible reach and influence with younger voters[7].

Artificial Intelligence (AI) is another form of GPT which has revolutionary potential but also has inherent risks[8]. At the time of writing, predicting the future use of AI lacks any form of certainty[9]. Whilst early AI dates back several decades, advances in computing processing power over the last five years have seen a massive acceleration in AI technological development and potential applications[10]. AI is now at an important juncture where its transformative possibilities are close to being realised, including within the health sector.

AI is playing an increasingly prominent role within our lives as each year passes by[11]. Each of us is likely to interact with AI technology on a daily basis, perhaps even unwittingly[12]. Your email provider almost certainly uses AI algorithms to filter mail into your 'focussed', 'other' and 'junk' folders[13]; AI automates a host of functions on your smartphone, from predictive text and voice recognition, to optimising your battery life. AI is also used extensively in online banking – recognising fraudulent activity and authenticating genuine transactions[14]; even basic internet searches are now AI-powered, where vast amounts of data can be summarised and structured intelligently, with accessible and intuitive overviews delivered at near instantaneous speed[15].

Defining Artificial Intelligence (AI)

Definitions of AI vary, however, in the broadest terms it refers to the simulation of human intelligence processes by machines, particularly computer systems[16]. AI may feel like a recent innovation, however its origins trace back to the early days of modern computing in the 1950s – its theoretical foundation goes back further still[17].

AI simulates human intelligence processes including *learning* – the acquisition of information and rules for using the information; *reasoning* – the use of rules to reach approximate or definite conclusions; and *self-correction* – continuous updating and improvement of information, rules, analysis and interpretation[18]. Perhaps the best-known collective use of these processes is when AI is used *generatively* to simulate a context-sensitive response or a conversation, for example, in the form of a 'chat' with a human[19].

AI within Public Health and healthcare systems

There is a growing appetite for using AI within strategies to improve Public Health outcomes[20]. The use of AI in Public Health has accelerated in light of its application during the coronavirus (COVID-19) pandemic[21]. Innovative AI-based datasets, surveillance tools and analytical models emerged quickly at the outset of the pandemic and were used in predicting the spread of COVID-19[22], and in supplementing understandings of public attitudes to lockdown measures and vaccination uptake[23]. In terms of its use within healthcare systems, AI is already in use within a limited range of NHS clinical services, including particularly within medical imaging and radiology[24].

Scotland has a robust Public Health infrastructure with a rich history of innovation and impactful use of health surveillance data, intelligence and progressive methodologies which have informed policy, practice and legislation[25-27]. AI has groundbreaking potential within Public Health and healthcare systems – where there are numerous ways in which AI technologies might be deployed within strategies to improve population health and address inequalities within Scotland[28].

The scale and range of potential uses of AI within Public Health and healthcare systems in Scotland will be discussed in this paper, however, there are potentially three overarching features of its application which are worthwhile outlining at this early stage.

These are:

- AI's ability to near-instantaneously analyse vast amounts of diverse, complex data[23], such as pertaining to population health, and to generate new learning and fresh insight;
- AI can supplement clinical practice and decision-making;
- and lastly, the ability of AI to facilitate a patient interface, that is, to effectively simulate a limited form of healthcare interactions with patients, providing evidence-based support, information and advice[29].

Purpose of this paper

This discussion paper is designed to stimulate engagement and conversation concerning the potential and future uses of AI within Public Health and healthcare systems in Scotland. The paper is designed to be an accessible introduction to some important concepts. The paper assumes no prior knowledge of AI or its application in Public Health or healthcare systems.

The paper uses current evidence and expert insights to consider the potential advantages of using AI within Public Health and healthcare in Scotland. The paper also discusses important risks and important practical, ethical, and moral considerations.

Methods

This discussion paper is shaped by an evidence scoping review of approaching 170 peer-reviewed publications concerning the application of AI within Public Health and healthcare systems. UK studies and peer-reviewed insights were prioritised in the review, however in some instances US papers and a limited number of international publications are discussed when considering broader concepts and learning points that are generalisable to the Scottish Public Health and healthcare contexts. A further four grey literature publications and briefings from Government and AI organisations were also reviewed.

To support reader engagement and ease of understanding, the key themes emerging from the evidence review have been grouped under eight key questions concerning the potential use and future application of AI within Scotland's Public Health and healthcare systems.

These questions are:

- 1. Why should Public Health and healthcare professionals begin learning about AI?
- 2. What AI capacity and skills exist in Scotland currently?
- 3. Is AI already in use within Scotland's Public Health and healthcare systems?
- 4. What are the likely positives and negatives of using AI within Public Health and healthcare systems in Scotland?
- 5. Is AI currently used to gather data from social media to support Public Health interventions?
- 6. How do patients feel about the use of AI within Public Health and healthcare systems?
- 7. What are the policy and governance arrangements concerning the use of AI in Scotland's Public Health and healthcare systems?
- 8. What are the opportunities and challenges in further embedding AI within Scotland's Public Health and healthcare systems?

Key questions concerning the use of AI within Scotland's Public Health and healthcare systems

1. Why should Public Health and healthcare professionals begin learning about AI?

The use of AI within Public Health and healthcare systems is developing at an extraordinary rate[30]. As AI technologies develop and evolve, so must the awareness and understanding among Public Health and healthcare professionals. In this space, the expertise of Public Health and healthcare professionals is needed now more than ever[31].

AI is already being utilised in transforming how we understand, prevent, and respond to health challenges on a global scale[32]. By engaging with and learning more about AI, even at a basic level, Public Health and healthcare professionals can more effectively shape the ways these tools are developed and applied to try to ensure they create meaningful, equitable, sustainable and ethical improvements to population health[33].

AI offers remarkable opportunities in Public Health and in healthcare systems: supporting clinical practice, predicting disease outbreaks, analysing large-scale health data, optimising resource allocation, and even personalising interventions to meet individual and community needs[34]. However, these AI applications will only be as effective as the understanding, data, evidence, insights, and ethical frameworks that underpin them[35]. Crucially, as will be discussed, health professionals have a vital role in identifying "algorithmic biases"[A] that may exist in AI model's "training data"[B] or the analysis undertaken by AI software. Health professionals must also consider advocating for, engaging and involving the general public, defined patient populations and those of protected characteristics, in order to represent their questions, hopes and fears within AI healthcare developments[36] – this will also be discussed in more detail below.

The need to authentically and meaningfully involve healthcare professionals as well as the public in AI reinforces the necessity for partnership within AI development. This has very much been the model for AI healthcare development in Scotland, where health professionals work collaboratively alongside AI technologists and academics (as described under Question 2, below). Within AI developments, Public Health and healthcare professionals must provide their understanding of the nuances of disease, health systems, community needs, the social determinants of health, and patient confidentiality and safety[37].

Leaving the development of AI solely to technologists, programmers and developers risks overlooking the context, equity, and humanity that underpins the Public Health

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[A] **Algorithmic bias** refers to systemic and repeatable features of AI systems that create unfair results, predictions and outcomes for specific individuals or groups. It can be caused by imbalanced training data, as well as decisions made during data collection and algorithmic design.

[B] **AI training data** is a collection of data or labelled examples that teach AI models how to recognise patterns and make predictions. It's the foundation for AI machine learning models.

profession and the NHS[38]. Upskilling in AI does not mean that Public Health and healthcare professionals and leaders have to learn programming or other technological skills. Instead, it means learning enough to collaborate effectively with technologists, ask the right questions, test assumptions and consider potential algorithmic bias within AI developments, and advocate for the use of AI in ways that equitably serve the public good.

By stepping into this space, Public Health and healthcare professionals are not only advancing their own skills but would be ensuring that equity, inclusion and safety are embedded at the heart of AI technological innovation within the NHS.

2. What AI capacity and skills exist in Scotland currently?

Scotland has seen a rapid expansion in AI research, leadership and development in recent years[39]. Indeed, Scotland has a long history of AI innovation – Glasgow's Turing Institute was an early pioneer of AI development as early as the 1980s[40]. Much of Scotland's groundbreaking AI work is undertaken in its universities. Over the past two decades, Scotland's universities have significantly advanced their AI capabilities and capacities, galvanising the nation's position as one of the global leaders in AI research and education. As of 2021, seven out of sixteen Scottish universities offer AI degrees at both undergraduate and postgraduate levels, and a further two offer AI degrees at undergraduate level only[41].

The University of Edinburgh hosts two British Government-funded hubs for next-generation AI innovation. The University of Edinburgh is also represented within a cohort of research teams, including one from the University of Glasgow, in developing responsible AI across education, policing, and the creative industries[C].

Academics from Scottish universities have contributed significantly to the development of Scotland's AI strategy (2021), which prioritises the development of trustworthy, ethical, and inclusive AI (further details can be found under Question 7, below). The strategy endorses the continuing role of higher education institutions in shaping AI policies and practices[41].

There has also been a range of specific AI research and development collaborations supporting Scottish healthcare. One such example is the pivotal development of

[C] **Edinburgh secures £24 million boost for AI innovation** - https://www.ed.ac.uk/news/2024/edinburgh-secures-ps24-million-boost-for-ai-innova

the Industrial Centre for AI Research in Digital Diagnostics (iCAIRD)[D] – a Scotland-wide initiative which has been developing and using AI within, primarily, clinical digital diagnostics[42]. iCAIRD brings together industrial technologist collaborators (Bering, Canon, Philips, Deep Cognito, Glencoe), and academic partners (the universities of Glasgow, Edinburgh, St Andrews and Aberdeen).

The Centre allows clinicians, academic researchers, health planners and industry partners to work together in supporting and developing AI to inform clinical questions, decision-making and practice. iCAIRD contributed effectively during Scotland's response to COVID-19, where AI was used in addition to existing infectious disease surveillance measures, to more accurately predict COVID-19 infection rates, determine optimal care pathways, forecast resource utilisation, provide clinical decision support, and ultimately respond quickly and effectively to the disease[43].

[D] **iCAIRD - the Industrial Centre for Artificial Intelligence Research in Digital Diagnostics**
https://www.woshealthinnovation.scot/exemplar-projects/icaird/

3. Is AI already in use within Scotland's Public Health and healthcare systems?

This question has posed challenges in answering and evidencing. Through normal online search criteria, we can find references to pilots of AI use in Scotland's Public Health and healthcare systems, within, for example, Scotland's AI strategy document[41]. However, it has not been possible to identify or source related evaluation reports within the public domain. It is apparent, though, that in addition to being deployed in the response to COVID-19[44], AI is already used in a limited number of healthcare research and developmental settings in Scotland[45]. Overall, these settings incorporate AI tools which interpret medical images, automate administrative tasks and predict and prevent diseases[46].

At the time of writing, and within the scope of this discussion paper, it is reasonable to say that there is always a 'human in the loop' within the current application of AI in healthcare within Scotland – where AI assists human health professionals and clinicians, rather than undertaking tasks independently[47]. Current AI technologies rely on human involvement for safety reasons and protocols exist to ensure that safety measures are consistently

applied[48]. The improved accuracy and efficiency of AI, used in supplementing traditional approaches and practice in these Public Health and healthcare contexts, is at present being researched, tested and evaluated, although this report highlights an overall lack of clarity and transparency.

AI is regarded as a promising tool in firstly, supporting healthcare providers and clinicians in decision-making. Secondly, it is also clear that effectively implemented AI has the potential to support healthcare systems and staff to cope with high levels of demand on services[49]. Scotland's AI strategy[41] cites two projects which demonstrate how AI has been used in healthcare systems in order to contribute to these two developmental areas, respectively:

In the northeast region of Scotland, AI has been used to enhance the interpretation of mammograms in breast cancer screenings[41]. The Northeast of Scotland Breast Screening Programme has partnered with iCAIRD and Kheiron Medical Technologies to explore the potential for AI to further improve the existing high standards of breast screening programmes in detecting cancers, producing results more quickly and delivering improved outcomes for women[E]. The AI programme developed has utilised and learnt from four years of anonymised breast screening images, comprising over 80,000 sets of mammograms. The project aims to establish how effectively the AI programme can supplement human diagnosis, identify very small cancers that may be missed by the human eye and reduce the number of women who are recalled due to inconclusive scan results.

Another example relates to the use of AI to support the mental health and wellbeing of young people. Referrals to Children and Adolescent Mental Health Services (CAMHS) have doubled since pre-COVID times, leading to unmanageable service demand, long waiting times and alarming levels of unmet population health needs[50]. Mental health stigma, alongside a lack of reliable and accessible information and preventative services that could help young people at the early onset of mental health conditions, is driving a growth in serious mental health issues among Scotland's young people[51].

A partnership between tech company Voxsio, NHS Forth Valley and groups of young people from Stirlingshire, has developed an AI-powered chatbot called Allichat, which is designed for and with young people to discuss mental health issues[F]. Allichat delivers information through the form of conversation using a combination of Natural Language Understanding (NLU)[G] and Machine Learning (ML)[H] AI. NLU AI software enables users to interact with a computer using speech and written text, while the ML AI allows the programme to learn and adapt from its own actions and improve its performance as well as learn patterns.

[E] **Scottish Breast Screening Programme: major review**
https://www.gov.scot/publications/major-review-scottish-breast-screening-programme/pages/9/

[F] **Voxsio – Allichat** https://www.nesta.org.uk/feature/ai-good-meet-grantees/voxsio-allichat/

[G] **Natural Language Understanding** (NLU) is an AI technology designed to enable computers to understand and respond to human language. NLU is a key component of many AI-driven applications, such as chatbots.

[H] **Machine Learning** (ML) refers to the use and development of computer systems that are able to learn and adapt without following explicit instructions, by using algorithms and statistical models to analyse and draw inferences from patterns in data.

In essence, Allichat helps young people to initiate a conversation about their mental health and can personalise evidence-based advice and support in order for individuals to better understand their own issues and to initiate proactive self-care. Voxsio's aim is to provide a safe space for young people to talk about their mental health using a programme that normalises discussion of common mental health conditions. This, in turn, is designed to help young people to cope better with mental health issues as they arise and before they escalate to a point where they need professional support, reducing the downstream demand for mental health services. At the time of writing, an evaluation of this project does not appear to be available within the public domain.

4. What are the positives and negatives of using AI within Public Health and healthcare systems in Scotland?

Fundamentally, effectively deployed AI technologies within Scotland's Public Health and healthcare systems can potentially save significant time and resources, as well as enhancing analytical capability, healthcare quality and patient outcomes[52, 53].

Firstly, the advantages of AI within Public Health are considered, by asking how can AI improve existing Public Health surveillance and response approaches?

Public Health surveillance appears particularly suited to several characteristics of AI analytical and processing power, not least that Public Health surveillance is intrinsically data driven[54]. Identifying timely, precise, and reliable signals of emerging health irregularities and disease outbreaks from a range of data sources has always been the primary goal of Public Health surveillance[55]. This presents three distinct challenges: first, sourcing robust data; second, developing and applying reliable analytic frameworks; and third – as underscored by the COVID-19 pandemic and the impacts of climate change – Public Health surveillance must become faster and more responsive to rapidly changing global health issues and crises[56]. AI provides a range of methods and techniques to potentially address all three challenges and the real-world complexities that exist therein[57]. The overarching appeal of AI in doing this is the near instantaneous speed with which it can support robust data capture and analysis[58].

An important point is that AI unlocks the potential to utilise a variety of novel or underexplored data sources within health surveillance purposes, often including those not intentionally designed to answer epidemiological questions[59]. For example, internet

search data, social media platforms (discussed specifically in Question 5) and device geographical sensing capabilities, can be utilised collectively to offer finely-tuned Public Health surveillance possibilities[60].

Another possible advantage of AI within Public Health surveillance is its ability to incorporate, systemise, and interpret a range of data forms beyond traditional numeric data and "structured labelling"[I] which forms the basis of statistical analysis[61]. AI can undertake this traditional statistical analysis and supplement the analysis and findings with new data types, including geographical movement data, unstructured and semi-structured text, images, and videos[62]. In the case of the COVID-19 pandemic, AI technologies utilised in this way have been cited as leading to a better understanding of predicted disease spread, infection rates and patient outcomes, public attitudes and behaviours in relation to lockdown measures, when to seek medical help, and vaccination uptake[63, 64].

There is growing interest, and an ever-developing range of publications in the interdisciplinary area of AI and Public Health surveillance[65]. Whilst the COVID-19 pandemic has accelerated the use of AI within Public Health surveillance, with many positive accounts of its usage in the UK[66] and beyond[67], we must also stress that some experts have highlighted a range of challenges, considerations and difficulties inherent in such analysis[68]. Concerns have also been raised as to the ethics and legalities within the approach[69]. At the time of writing, the onset of the pandemic was five years ago, during which time the development of AI technologies in this field have developed even further and at an unprecedented rate[70].

The type of AI generally used to incorporate and analyse diverse and complex forms of data, such as is described here during the pandemic, is known as "generative AI"[J, 71] – popular forms of which include ChatGPT[72]. Generative AI is a form of AI that essentially creates new content and ideas from data supplied to it. Generative AI outputs can include summaries, recommendations and findings, but can also include conversations, stories, images, videos, and music. Generative AI is susceptible to the algorithmic biases described already and to "AI hallucinations"[K, 73] where seemingly random, erroneous and sometimes dangerous findings and recommendations are occasionally generated[74], although the exact definition and use of the term across different AI applications is debated[75]. This review has even encountered a paper where generative AI produced convincing, yet completely false, publication references to support the summary points it was making[28]. Generative AI machine learning has also been shown to be susceptible to external attacks or "data poisoning"[L] – essentially, a cyberattack that targets the foundation of an AI system by purposively poisoning its training data[76].

[I] **Structured labelling** – A systematic approach to annotating data with predefined categories or attributes, ensuring consistency and accuracy for AI training and analysis.

[J] **Generative AI** – AI systems that create new content, such as text, images, audio, or code, by learning patterns from large datasets.

[K] **AI hallucinations** – Instances where AI generates false, misleading, or nonsensical information, presenting it as factual.

[L] **Data poisoning** – in AI software development, it refers to the intentional manipulation or corruption of training data to deceive or degrade the performance of a machine learning model. It is a type of adversarial attack aimed at introducing vulnerabilities or biases during the model's training phase.

By contrast, the nature of AI development and usage within healthcare systems and clinical settings, in general, requires a more contained, often "nongenerative AI"[M] form of Supervised Machine Learning[N, 77] and processing, which tends to repetitively utilise narrower fields of specialised data[78]. The often-cited and best available example of this AI is its use in supporting clinical interpretation of medical imaging, and subsequent treatment decisions, and even related administration and appointment planning[79]. The Northeast of Scotland Breast Screening Programme is a successful usage of this narrower, nongenerative form of AI (described in Question 3).

In broad terms, and within the scope of this paper, we can be clear that nongenerative forms of AI usage in healthcare appear to be positively reported and far less contested, with few reports of risks or negative impacts[80]. Indeed, some experts describe how these nongenerative forms of AI, once accepted and safely used in clinical practice, simply become known as clinical software[O].

One of the main advantages of nongenerative AI techniques is their simplicity of use with much higher interpretability[78]. Unlike generative AI models, where there is very limited scope for understanding the basis of an algorithm's output, nongenerative approaches provide explainable results via a range of techniques often termed "explainable AI"[P, 81]. Supporting transparency is critical to enable clinicians to trust the output of algorithms and to reflect and understand how they arrive at a diagnosis, decision or prediction[82]. High-quality nongenerative AI techniques also offer reliability and robustness, as they are less susceptible to generating erroneous patterns and findings[83]. In contrast, generative AI models, as described, can be prone to biases within training data (or such biases may be difficult to detect and reverse) and may therefore produce unrealistic or misleading results[84]. Furthermore, nongenerative AI applications are more efficient and require fewer resources than generative models, making them more accessible to clinicians without considerable investment in computational infrastructure[85].

Another important advantage of nongenerative AI is that it provides more reproducible statistical reliability and assessment measures, allowing for a more familiar and transparent understanding of their performance measures, and limitations, within clinical settings[86]. In contrast, generative AI models can be difficult to evaluate, as they often produce complex outputs that cannot be quantified or compared. Nongenerative AI techniques also enable the use of established statistical methods for hypothesis testing and confidence interval estimation, providing a robust framework for assessing the significance and uncertainty of results[87]. This systematic reliability is essential in healthcare, where clinicians need to make informed decisions based on evidence.

[M] **Nongenerative AI** – AI models that analyse, classify, or make decisions based on existing data without generating new content.

[N] **Supervised Machine Learning** – A type of machine learning where an AI model is trained, with human supervision ensuring accuracy within inputs and outputs, and acting as a safeguard against errors and biases in the learning process.

[O] **Hetan Shah**, Chief Executive Officer of the British Academy in Health Foundation REAL lecture, 13th February 2025 - https://www.health.org.uk/events/hype-hallucination-hope-what-might-ai-mean-for-our-health

[P] **Explainable AI** – AI systems (often nongenerative AI) designed to provide transparent and interpretable reasoning behind their decisions, which can be assessed using established statistical approaches, which improves trust and accountability.

Nongenerative AI does however rely on medical data sets which often suffer from missing values, and inconsistencies, which can adversely impact the performance and reliability of models[88]. For example, electronic health records may contain errors or omissions due to manual entry or system glitches, whereas imaging data sets may be affected by variations in image acquisition protocols or equipment[89].

To summarise, some experts even refer to generative AI as "black box" computational processing – that is, there is a lack of transparency and comprehensibility concerning how the generative AI algorithms work and learn and how findings are generated[90]. In contrast, nongenerative AI can be referred to as "white box", meaning they are more, transparent, understandable and their outputs and workings can be traced and scrutinised[91] – although the terms 'black' and 'white' box AI are not universally accepted.

However, we also note an extensive range of pilots and trials of nongenerative AI within healthcare settings, without clear evaluation outputs[41]. In general, it could be considered that there is a lack of transparency in clearly assessing (particularly) the shortfalls of nongenerative AI within healthcare settings.

5. Is AI currently used to gather data from social media to support Public Health interventions?

It is beyond the scope of this paper to accurately characterise the extent to which AI has been used to gather and analyse social media data, although it appears that applications of this approach have been limited in the UK to date, and almost entirely related to the COVID-19 pandemic response[23]. In recent times, Public Health surveillance has begun incorporating novel datasets from online social media platforms, such as X (formerly Twitter), to enhance the timeliness of acquiring health data[92]. These forms of data have sometimes been referred to as "social big data"[Q] – and are cited as being a real-time and cost-effective data source within Public Health surveillance[93].

Data relating to health and public opinion on health issues have been gathered from social media platforms, such as X and Google Trends, and used to observe diseases, forecast outbreaks, and understand Public Health emergencies[92]. For example, researchers have

[Q] **Social Big Data** – Large-scale data collected from social media, online interactions, and digital platforms, often used for AI-driven insights into human behaviour and trends, including recent forms of public health surveillance.

used tweets about conversations of HIV risk behaviours to predict diagnosis outcomes[94]. Similarly, in response to the opioid crisis in parts of the USA, Public Health researchers monitored opioid conversations on X to identify popular terminologies and consumption methods across regions in order to support clinical interventions[95].

One of the main advantages of using AI to incorporate and analyse social big data, in supplementing traditional methods of health surveillance, is that it is real time and instantaneous[96]. Traditional epidemiological data sources and established analysis techniques alone involve significant delays in reporting[97]. For instance, the national and regional reporting of many diseases and chronic conditions are annual – meaning that policy maker and practitioner responses, including prevention and early-intervention approaches, can have limited impact[98]. The timeliness of AI-enabled social big data analysis in supplementing existing Public Health surveillance proved effective in responding to COVID-19 (including within the UK[99]) and is regarded as having significant potential in responding to natural disasters and future Public Health emergencies[100].

AI deployed in this way with social big data adopts NLU algorithms for "sentiment analysis"[R] and topic classification tasks. NLU approaches to health surveillance do however present unique challenges relating to bias that may differ from those found in traditional health surveillance methods[101]. When using AI algorithms to analyse social big data, bias within an algorithm may result within the data collection process[102]. Data collection may present a lack of representativeness among some population groups or misrepresent populations. It may be the views and experiences – and therefore the data – for example from older people, those experiencing poverty, and those with disabilities that are missed within data collection as they may not have access to the internet or the inclination or skills to engage with social media[103].

Research studies that use X's application programming interface to extract tweets require the development of a search query[104]. Keywords or hashtags selected for this data extraction process may misrepresent populations if words of interest do not encompass the vernacular of each subregion or population of interest[105].

Human biases may also pervade into AI data, algorithms, and models directly from social media which have been used for Public Health surveillance[106]. NLP models are typically trained on huge datasets generated by users that make up society; the biases they exhibit are often indicative of societal perceptions towards certain social groups or identities, including sexism, homophobia, racism and ablism for example[107]. There is an increasing need to learn how to identify and address problems resulting from the utilisation of generative AI use of social data. This need will continue to grow as newly-accessible generative AI tools, such as ChatGPT, become more widely used among the general public[108].

[R] **Sentiment analysis** refers to the use of AI natural language-understanding or processing techniques to identify and categorize the emotional tone or attitude expressed within a piece of text, whether it be positive, negative, or neutral.

6. How do patients feel about the use of AI within Public Health and healthcare systems?

While there have been significant advances in the use of AI technologies within healthcare, importantly, to date and within the scope of this paper, we find limited engagement with UK patient groups, or indeed the general public – both of whom will be impacted by applications of AI in Public Health and healthcare systems.

This is concerning from an ethical standpoint but is also troubling since patient worries about AI could present a significant barrier to the longer-term use and acceptability of these tools[109]. Studies of nonmedical applications of AI have shown that the public can have diverse and often polarising views, with factors such as media coverage and early experiences playing key roles in shaping public opinion[110].

Furthermore, the limited range of studies that have assessed patient views have focussed on a very constrained array of AI developments with explicit patient awareness and consent, which restricts their utility as a benchmark in anticipating wider patient opinion and engagement with other AI applications in healthcare[111, 112].

Given that the general patient population and defined patient groups are the intended beneficiaries of these health sector AI innovations, understanding their needs, values, and priorities is vital in ensuring that AI technologies are well-received, but also are developed and applied in an ethical way that improves population health and patient care[113].

Even in situations where patients do not interface directly with AI technologies – such as within Public Health predictive analytics (as deployed during the COVID-19 pandemic) – patients still endure the largest risk, should implementation be done inaccurately or unethically[114]. Given the extent to which patients are forced to accept the hypothetical risks associated with novel applications of AI in Public Health, there is therefore an ethical obligation to ensure that patient values and needs are incorporated into implementation plans[115].

A 2021 qualitative study in the US concerning patient views on diverse AI applications within healthcare makes clear that, while patients are supportive about the potential of AI improving their care, they are also worried about the safety and governance of healthcare AI[109]. Study respondents emphasised the importance of transparency, patient choice, the costs of AI developments, questions about data quality, and the security of AI within healthcare. Participants also urged caution in developing and implementing AI tools. They reported a need for a careful transition phase to ensure that any AI tool used in their care is well-tested and precise[109]. Participants also called for oversight and regulatory protections against possible harms. While patients were unsure as to the specifics of what these

regulations should include or who should enforce them, they felt that new and additional protections were essential for AI tools. Collectively, these points are mirrored in similar studies[116].

Participants also felt strongly that their clinicians should act as a safety measure to buffer patients from the potential harms that might result from mistakes made by healthcare AI[109]. One overarching point commonly expressed was in terms of their healthcare providers retaining final discretion over AI-generated treatment plans or analytics, and maintaining responsibility for patient care and safety[117]. Other participants were comfortable extending more authority to AI tools but still calling for "checks and balances" or "second opinions" on recommendations generated by healthcare AI[118]. The majority of participants felt strongly that AI should not have the ability to act autonomously in a clinical setting, stressing that both treatment decisions and the monitoring of ongoing care should be done by a human provider – patients were clear than humanity and empathy must remain at the heart of clinical care[118].

Participants asserted that the preservation of choice was imperative to their overall comfort with applications of AI in healthcare. They expressed that patients should have the right to choose to incorporate AI in their care or in the use of their healthcare record and to have the right to opt-out of AI involvement if they so decide[109]. Related to this, was a strong overarching point that patients demand more transparency concerning AI, they want AI's use in their healthcare to be explainable[119, 120].

Participants also demonstrated a clear understanding of the impact of data quality on AI tools and their clinical or predictive analytic recommendations[109]. Patients had several concerns related to the way healthcare AI might be developed using flawed datasets, potentially resulting in harm to patients[121]. They felt data from electronic health records was not accurate enough to be reliable in training healthcare AI, citing their own experiences with errors they had found in their own health records – or that digital health records do not capture the nuance and lived experience of health conditions[122]. Patients were also concerned about a systems-level crash or mass technological failure, and the impact this might have on a clinical system that is heavily reliant on AI tools[123].

7. What are the policy and governance arrangements concerning the use of AI in Scotland's Public Health and healthcare systems?

At the time of writing, the UK has refused to sign the Paris Summit (February 2025) global declaration on the regulation and governance and use of AI. The declaration sets out an ambition to reduce digital divides by promoting AI accessibility and ensuring the development is "transparent", "safe", as well as "secure and trustworthy". A UK Government spokesperson was cited in the media as stating *"we felt the declaration didn't provide enough practical clarity on global governance, nor sufficiently address harder questions around national security and the challenge AI poses to it"*[S].

The Scottish Government aspires to promote the use of *"trustworthy, ethical and inclusive AI"* across health and social care, as outlined in Scotland's AI Strategy[41], the Digital Health and Care Strategy 2021[124], and Scotland's Data Strategy for Health and Social Care 2023[125]. Scotland's AI Strategy is explicitly guided by the Organisation for Economic Cooperation and Development's (OECD) five complementary values-based principles[T] for the responsible stewardship of trustworthy AI. These are that:

- AI should benefit people and the planet by driving inclusive growth, sustainable development and wellbeing.
- AI systems should be designed in a way that respects the rule of law, human rights, democratic values and diversity, and they should include appropriate safeguards – for example, enabling human intervention where necessary – to ensure a fair and just society.
- There should be transparency and responsible disclosure around AI systems to ensure that people understand AI-based outcomes and can challenge them.
- AI systems must function in a robust, secure and safe way throughout their life cycles and potential risks should be continually assessed and managed.
- Organisations and individuals developing, deploying or operating AI systems should be held accountable for their proper functioning in line with the above principles.

[S] **US and UK refuse to sign Paris summit declaration on 'inclusive' AI** - https://www.theguardian.com/technology/2025/feb/11/us-uk-paris-ai-summit-artificial-intelligence-declaration

[T] **OECD AI Principles overview** - https://oecd.ai/en/ai-principles

The Scottish Government and COSLA's Data Strategy for Health and Social Care (2023) aims to bring forward a framework of appropriate guidance, support, standards and regulations for the ethical and safe deployment of AI-based developments within the health and social care sector[125]. Overall governance of the national approach to AI in health and social care sits with the Data Board for Health and Social Care[U].

Within NHS Scotland, most AI projects take place within geographical NHS Boards, while some national Boards, including NHS Golden Jubilee and NHS Health Improvement Scotland, also play a role. AI development is usually driven by the NHS Regional Innovation Hubs, in cooperation with academic and industry partners, as described in the examples provided in Question 3.

[U] **Scottish Government Health and Social Care Data Board** - https://www.gov.scot/groups/health-and-social-care-data-board/

8. What are the opportunities and challenges in further embedding AI within Scotland's Public Health and healthcare systems?

The use of more contained, primarily nongenerative forms of AI within clinical settings, such as in supporting clinical decision-making with medical images, appears to be emerging as an area of significant opportunity in Scotland, with lower reports of risks[126]. Pilots and trials of AI in this field do exist in the UK, and there are some positive peer-reviewed international publications to support its use[127]. However, there appears to be a lack of evaluative capacity surrounding AI healthcare developments, in general[128] and in Scotland. There is an opportunity for Scotland to address this deficit and to further, and potentially lead, the understanding of not just whether AI works to enhance, for example, clinical judgements in cancer screening imaging, but also to gain vital insight and learning as to how it can be successfully embedded within complex and stretched health systems globally[129].

Relatedly, the use of predominantly nongenerative AI within healthcare administration is another area that receives positive commentary across peer-reviewed journal publications[130]. This presents an opportunity for Scottish Health Boards to better

understand how such administrative service redesign can best utilise and implement AI to enhance efficiency and accuracy. This would require investment in three areas: service-redesign capacity and skills; appropriate AI technology; and evaluation capacity – incorporating both skilled healthcare systems understanding and AI knowledge and insights.

This issue of using AI to enhance the efficiency of healthcare administration should lead to discussions relating to the NHS workforce. Within the scope of this paper, it appears that pragmatic discussions on how efficiencies will be made, are largely missing from AI rhetoric within Scotland. In the short-term it may be that efficiencies support existing NHS staff and make the running of services smoother, faster and less stressful[131]. The logical view however, is that, if, in the future, AI could safely replicate some administrative functions within the NHS, with greater speed and accuracy than humans, then it would reduce the need, and the cost, for NHS staff to fulfil these duties[132]. On the other hand, if AI is embedded within healthcare systems, such as within administrative functions, it may support the creation and demand for specialist AI roles[133].

There are several difficulties to be resolved to ensure the safe and successful further application of generative AI within Scotland's Public Health systems. These include ethical and legal concerns, particularly in relation to the central issues of patient data, social big data, consent, security, and privacy[134]. In broader terms, issues relating to liability concerning the use of generative AI within the health sector are also a paramount concern[135]. Who would be responsible if a machine learning algorithm funded, for example, by the Scottish Government, developed by a technology company, supported by an academic partner and evaluated and implemented within an NHS setting, wrongly informs Public Health decision-making?

As previously described, ethical implications also concern algorithmic bias and discrimination embedded within AI-based systems, which can lead to skewed findings and ultimately can disproportionately harm vulnerable people and groups[136], including LGBT+ people, disabled people and racialised minorities groups, which are already underrepresented within Public Health data, policy and research[137-139]. This underrepresentation includes inadequacies in data collection within mainstream services which have masked several health inequalities and unmet health needs[140]. Without deliberate and concerted efforts to address these biases within Public Health data sets and thus within AI training data, AI algorithms will tend to update and replicate previous systemic forms of discrimination and bias[89].

These forms of bias are also likely to be included in analysis of social big data within AI Public Health algorithms[23] (as discussed in Question 5). Social media platforms can be toxic and aggressive platforms, where homophobic, anti-disability, sexist and racist views are expressed freely and are often reinforced by others[141-143]. The inclusion of social media data in such analysis must also be cognisant of the barriers that may prohibit some population groups such as those experiencing poverty, older people or those who are visually impaired from engaging and participating in these digital platforms – and therefore their views and insights are not captured in social big data[144].

Scotland has the opportunity to embed improving population health and the explicit and concerted drive to address health inequalities as the overarching values which underpin all aspects of AI development policy in Public Health and healthcare systems. It is worth making the pragmatic point that AI won't do this by itself.

The absence of basic comprehensibility and transparency surrounding generative AI-based systems is one of the main issues facing Public Health applications of AI[145]. Public Health policy makers and practitioners may find it challenging to fully comprehend how the AI algorithm arrives at its conclusions and recommendations. Only by working through every step of the algorithmic development with the technologists involved, and through close inequalities scrutiny of training data, can transparency and avoidance of bias be achieved[146]. This would be time consuming, thereby limiting one of AI's most appealing characteristics – its near instantaneous speed of analysis of large data sets, at least in the short term[147]. The lack of transparency described here fosters scepticism about the use of generative AI in the Public Health field[148].

The use of patient data from multiple sources is thought to reduce bias and enhance the diversity and comprehensiveness of AI models, resulting in more accurate and adaptable algorithms[149]. However, this practice must be accompanied by rigorous data de-identification, aggregation, and anonymisation protocols to safeguard patient privacy[150]. Collaborative efforts involving data sharing through developing techniques like "federated learning"[V] show great promise, where potentially several AI applications share their analysis, findings and learning without sharing any raw patient data[151]. This technique ensures that data remains within its source institution while contributing to the development of a powerful, collective AI model[152].

There may also be some challenges relating to national "AI adoption"[W], such as the possibility that AI tools trained with data from other countries must be recalibrated for the local population before they can be used in a specific location such as Scotland[153]. Issues such as the need for substantial investments in infrastructure, workforce and training are also critical considerations in taking forward AI development within Public Health and healthcare systems in the UK[154]. Furthermore, AI computing, particularly generative forms, consumes vast amounts of electricity, primarily due to the energy-intensive nature of training and running large machine learning models[155]. The demand for powerful data centres, which require constant cooling and operation, contributes to significant carbon-based emissions[156] which conflicts with Scotland's emission reduction targets within the Climate Change (Scotland) Act 2019[X].

[V] **Federated learning** – A machine learning approach that enables multiple devices or organizations to collaboratively train AI models without sharing raw data, enhancing privacy and security.

[W] **AI adoption** – The process of integrating AI technologies into business operations, products, or services to enhance efficiency, decision-making, or innovation. It involves organisational readiness, strategy, robust ethical and safety governance and the careful implementation of AI tools within existing or redesigned systems.

[X] **Reducing greenhouse gas emissions: Scotland's Climate Change Plan** - https://www.gov.scot/policies/climate-change/reducing-emissions/

What this paper adds

This is an introductory discussion paper to a technical, expansive and rapidly developing topic. The paper seeks to bridge a gap between specialised peer-reviewed evidence within the field of AI development and the understandings of health professionals and members of the public.

The paper is structured around eight key questions which have emerged from the analysis of the evidence reviewed. The paper is written in this way to support engagement and ease of understanding of key concepts and considerations concerning AI's application within Public Health and healthcare systems. This is important as the meaningful and sustained involvement of health professionals within the development of AI within the health sector is vital, now more than ever.

This paper seeks to raise a range of timely and important strategic and practical considerations regarding how people in Scotland wish to use AI to enhance Public Health and healthcare capabilities, capacity and efficiency. To this end the paper aims to be useful in both policy and practice spheres.

By using this paper to learn more about AI, even at an introductory level, Public Health and healthcare professionals can more effectively participate in discussions with AI technologists. The paper could also be used by members of ethics committees, including lay people, to support their comprehension and critical awareness of AI-based ethics applications. These uses, in turn, can support the ways AI tools are developed and applied to ensure they create meaningful, equitable, sustainable and ethical improvements to population health.

Limitations of this paper

The field of AI application within Public Health and healthcare systems is vast and rapidly developing, where new concepts and innovations can quickly change the prevailing narratives.

In response to this context, this paper has reviewed longer established fundamentals within AI development, which should equip the reader with a grasp of important concepts irrespective of the speed of change within the field. However, it remains possible that some evidence, insights and concepts may have been overlooked.

To support reader understanding of what is an expansive, and technically framed, evidence base, this paper aims to provide a concise and digestible view of some concepts. For example, whilst overarching points are confidently made, the clear delineation of generative and nongenerative AI and “black box” and “white box” processing transparency is reported in simplified terms.

A lack of accessible information concerning real-life applications of AI within Scotland’s health sector was also noted. It may be that these pilots and trials are, at the time of writing, ongoing, and have not yet yielded evaluation reports. However, this lack of transparency pervades the available AI in healthcare evidence base and indeed is inherent within some forms of AI itself.

Discussion

AI hype and transparency

It is hard to imagine a discipline of science and technology that has been surrounded by so much hype, confusion, fear and misinformation as AI[157]. This is perhaps due to AI's frequent, and at times malevolent, depiction within popular science fiction culture over the last 50 years[158]. It is also important and reasonable to be cautious, given that AI has a history of repeated boom/bust cycles, where initial excitement and optimism concerning its uses in a variety of settings and sectors has often faltered during its troubled real world applications[159, 160].

Indeed transparency, or at times, a lack of it, is an important theme surrounding the ever-developing role of AI in our lives and its use within Scottish Public Health and healthcare settings. This review has encountered difficulties in finding, at times, even basic information on AI pilots and trials within Scotland's health sector, much less any form of comprehensive and up-to-date overview. Whilst this is unlikely to be "AI creep"[Y], it does reflect a lack of concerted attention concerning public awareness and understanding of Scottish health sector AI developments.

Unpredictability within the AI revolution

AI is a powerful form of GPT, much like the internet, electricity or the steam engine; transformative innovations that have reshaped entire economies and societies. As AI continues to evolve and expand across industries including the health sector, its impact appears to be potentially revolutionary, ushering in what some are calling the "AI revolution"[Z]. By drawing parallels to the industrial revolution, we can better understand the nature and scope of the profound shifts AI may bring. We have identified three core areas in which the AI revolution differs from the industrial revolution:

- **Unprecedented levels of autonomation.** The industrial revolution focussed on mechanisation – where machines replaced physical labour but were still entirely dependent on human oversight. By contrast, the AI revolution seeks to automate not just some forms of physical labour but also human cognitive tasks, including decision-making, problem-solving,

[Y] **AI creep** – The gradual and often unnoticed expansion of AI into more areas of daily life, sometimes raising ethical, privacy, or societal concerns.

[Z] **AI revolution** – The transformative shift in industries and society driven by AI advancements, reshaping economies, healthcare, education, and labour markets.

and even creativity. The complete understanding of the automation involved in generative AI is limited to experts and even then, is not always transparent[161].

- **Speed of innovation.** During the industrial revolution, innovation was gradual, requiring infrastructure changes, resource extraction and related policy, regulation, governance and unionisation. Within the AI revolution, progress is exponentially faster due to the digital nature of AI models that can be trained and deployed with minimal material or time costs. Policy, regulation and governance can struggle to keep pace with AI developments[162]. A lack of transparency across AI development may mean that policy makers lack the skills, capacity and understanding to responsively ensure effective and safely regulated AI[163, 164].

- **Global scope of impact.** The industrial revolution affected industries tied to manufacturing, transportation, and agriculture. In stark contrast, the AI revolution is truly global in its scope and depth of reach – affecting almost every sector, including finance, education, medicine, law, and entertainment, as well as societal structures like politics and personal relationships[165].

These characteristics of AI as a GPT further emphasise the unpredictability of future AI applications and use, and heavily underscore the pivotal importance of ensuring that the AI revolution is safe, ethical and trustworthy, particularly its implementation within Public Health and in healthcare settings which must also be public facing, patient-centred, inclusive and equitable.

Engaging the public in health sector AI developments

Some of the rhetoric surrounding AI could be described as imbued with "technological arrogance" [AA, 166]. Some technologists appear steadfast in the view that AI will inevitably transform and permeate every facet of society in an unwaveringly positive way. This biased perspective is further evident when we consider that much AI development, discussion and debate within technological spheres is technocratic, and lacking transparency and deliberative attempts to connect with or consult the general public or patient groups (when deployed within defined healthcare settings). Some of the peer-reviewed literature cited in this report (particularly in relation to AI's role in COVID-19 responses) focussed on descriptions of what AI can do, often in specialised, technical and inaccessible terminology.

[AA] **Technological arrogance** – The overconfidence in technology's ability to solve complex problems, often overlooking ethical, social, or unintended consequences.

Within the scope of this review, a lack of evaluative coherence, capacity and assessment concerning AI's use within both Public Health and healthcare settings in Scotland is noted. The use of AI in these settings in Scotland and the UK has been described by some experts as repeated pilots and trials with limited contribution to the evidence base or public awareness and understanding.

In the face of such "technocratic elitism"[BB], further pragmatic and grounded questions, such as those that might be posed by the general public or defined patient groups, are an essential countenance. In relation to the use of social big data within generative AI in COVID-19 surveillance and response planning (outlined in Question 5), important questions might include:

"How reliable and useful was data gathered from social media within COVID-19 response planning?"; "Did the incorporation of social big data in COVID-19 response planning reduce the spread of the disease in Scotland?"; "How aware were social media users that their views, pictures and videos were being used in COVID-19 response planning, and what proportion of users would knowingly agree to this?".

Relating to Voxsios' Allichat app to support teenage mental health (as detailed in Question 3), important questions might include:

"How did the young people involved in the app trial feel about speaking about their mental health to a machine rather than a person?"; "Did the AI model generate any spurious recommendations or advice for the young people involved?"; and *"How accepting is society overall as to the use of a generative AI machine to support the mental health of young people?".*

At present, there appears to be no robust local evaluation available to answer these questions, nor any mechanism through which public can ask questions like these.

Based on the evidence review, we endorse a concerted effort to engage and consult the public in the use of AI within Scotland's Public Health and healthcare systems. A well-informed and engaged public may well be accepting of nongenerative forms of AI in clinical settings and may also set the bar as to the level of risk they are willing to accept in terms of generative AI use in Public Health surveillance, for example. The wisdom, insights and diversity of the public must inform AI's use within the health sector in Scotland.

◉ *AI implementation – learning from the past*

This is particularly true when we consider that there are notable examples of unsuccessful IT investment and innovation within the public sector which, at the time, were led by technologist experts and billed as efficiency driven, customer-focussed and designed to reduce the burden on public services. The failed implementation of Universal Credit's

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[BB]**Technocratic elitism** – The belief that experts and technologists should dominate decision-making, sometimes at the expense of public, democratic or diverse perspectives.

real-time IT systems led to in the region of one billion pounds in wasted spending. Various reports, including those from the National Audit Office[CC] and the Public Accounts Committee[DD], criticised the program for poor planning, ineffective project management, and repeated technical failures.

Learning from poorly designed and implemented, technologically-driven initiatives in public services is imperative. AI, like any other technology, is not magic or a silver bullet. AI, in and of itself, cannot enhance patient outcomes, reduce NHS waiting times or lessen the burden on stretched NHS services.

Instead of marvelling at what AI can do, public services must fundamentally consider: *"What do we want to achieve from service redesign?"; "How can patients inform this process?";* and *"How can technology, including AI, safely and ethically support the redesign of services enabling increased efficiency and/or accuracy?"*

Attempting to "shoehorn" AI technology into existing service designs, in the hope that it will somehow improve outcomes because it is the latest innovation, is likely to be a waste of time and resource.

◉ *Inclusive and equalities-sensitive AI in healthcare*

This review has discussed the potential for algorithmic bias within generative AI and how this risk is largely minimised within nongenerative AI, which has been primarily used within medical imaging. Within this field, there appear to be many examples of AI being successfully embedded within healthcare delivery systems[167]. The implementation of AI within healthcare systems represents an opportunity to consider bias and equalities within the whole system overall. For example, evidence tells us that racialised minorities populations, and those from the LGBT+ community are far less likely to attend routine screening appointments, such as mammograms, due to a range of barriers and prejudice they may encounter within healthcare settings[168, 169]. It may be that future iterations of AI within such screening services can be used to systemically identify these biases, barriers to engagement and unmet health needs.

◉ *AI within the wider determinants of health*

The evidence covered in this discussion paper relates primarily to the use of AI in Public Health and healthcare settings. At present there is a lack of consideration as to how AI can support improved outcomes shaped by the wider determinants of health and health

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[CC] **National Audit Office, Universal Credit: early progress report – value for money** (2013) - https://www.nao.org.uk/reports/universal-credit-early-progress-2/?nab=1

[DD] **Public Accounts Committee, Universal Credit inquiry** (undated) - https://committees.parliament.uk/work/3953/universal-credit-inquiry/

inequalities, including income (poverty), employment, place, community, education, sustainability and travel. A further useful question for investigation in this sphere might include:

"How can AI be used to mitigate the impacts of poverty?"

◉ *Scotland's AI strategy*

Issues relating to AI evaluation capacity, public engagement and consultation in AI development and use, AI implementation within complex services, and the role of AI within the wider determinants of health should be considered within Scotland's AI strategy[41] which is due for renewal in 2026. The 2021 Scottish AI strategy is broad and all encompassing, setting out important pillars which underpin a vision concerning the safety, ethics and reliability of AI use in Scotland. Future iterations of the strategy should consider the strategic and practical issues concerning AI development and use within the health sector, and how they relate to the wider determinants of health and diverse populations. It may be that these issues require and merit a specific Scottish AI in health strategy.

Conclusion

AI presents transformative opportunities for Scotland's Public Health and healthcare systems, offering enhanced diagnostic capabilities, improved efficiency, and more personalised patient care. By harnessing AI responsibly, Scotland can drive innovation while ensuring better health outcomes for all. However, these advancements must be approached with caution, acknowledging the risks of algorithmic biases, the challenges of integrating AI within complex and stretched NHS systems and structures, and the need for robust ethical and legal frameworks to address issues of accountability and liability.

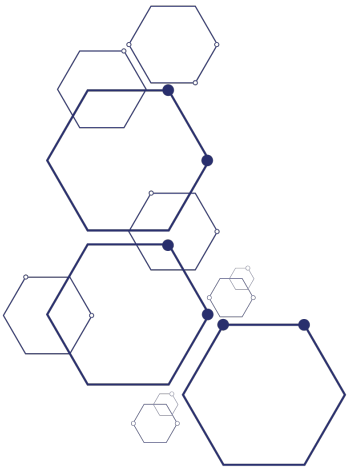
Public awareness, consultation and trust are essential, and this can only be achieved through transparency, engagement, and ensuring that AI serves as a tool to support, rather than replace, the humanity at the core of effective healthcare.

By learning from past public sector IT failures and embedding AI within a well-governed, inclusive, and patient-centred framework, Scotland can potentially lead the way in balancing technological progress with ethical responsibility. Investing in AI should not come at the expense of human compassion, clinical judgment, or healthcare policy and practice which explicitly seeks to address health inequalities. Instead, by fostering public awareness, collaboration, ensuring rigorous oversight, and prioritising patient safety, Scotland can build a future where AI enhances, rather than diminishes, the core values of the NHS.

Recommendations

Based on the evidence reviewed in this paper and on very recent expert narratives in this field[EE] the “one ask” of Scotland’s Cabinet Secretary for Health and Social Care, stemming from this report, is: to enhance public trust, awareness and consultation efforts concerning the development and implementation of AI in Scotland’s Public Health and healthcare systems. Specifically, this could involve:

- Developing a central Scottish AI in health repository to store accurate and timely information on all AI in health innovations, pilots and trials, updates and evaluation outputs. This could be disaggregated by Health Board and include scientific, Public Health and clinical learning, as well as accessible summaries designed for the public or specific patient groups.
- Boosting Scotland’s AI evaluation and research capacity within the health sector – this would dovetail with a Scottish AI in health repository, where researchers and evaluators would be better connected nationally, pooling resources, learning and insight and promoting efficiency.
- Delivering effective research and evaluation which is acutely focussed on AI implementation within complex NHS systems. Such appraisals must be patient-centred, incorporate the views of NHS clinical and delivery staff and be systems-focussed in response to clear efficiency, accuracy and safety objectives; rather than being overly technologically or AI-led.



[EE] **Hetan Shah**, Chief Executive Officer of the British Academy in Health Foundation REAL lecture, 13th February 2025 - https://www.health.org.uk/events/hype-hallucination-hope-what-might-ai-mean-for-our-health

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