Artificial intelligence and health inequalities: a summary of the evidence

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1 Summary: Artificial Intelligence and health inequalities

This report outlines what is known about Artificial Intelligence (AI) and health inequalities, with particular emphasis on findings relevant to the UK. It explores the range of different uses of AI, general perceived opportunities and risks and then explores how the use of AI in healthcare could impact different groups of people known to experience health inequalities. While definitions of AI often refer to the ability of a machine to display human-like capabilities such as reasoning, learning, planning and creativity, there is currently no standard definition that has been widely adopted. For the purpose of this report, we have adopted this broad definition to reflect the diversity of work underway.

The review indicates that there are many ways that AI could be used to support healthcare provision, and that both healthcare professionals and the public are open to exploring its use, as long as appropriate safeguards are in place. The wide range of uses, and the relative unfamiliarity with the technology means that views may not be fixed, and that high profile successes (or failures) could impact on attitudes and behaviours.

The way that AI is trained and used is likely to impact on the way it affects health inequalities. If the AI has been trained on a diverse data set and used by a healthcare professional to support the provision of care, it can potentially have a positive impact. However, if there are issues with the training data, or data about the patient then there is potential for inequalities to be increased.

Similarly, there are some groups that are likely to find it easier to access healthcare through the use of AI e.g. young people, speakers of languages other than English. However, these groups may have lower levels of trust, and high expectations of privacy and security for their data. Others (older people, people without internet access or skills, including those experiencing poverty, homeless, and gypsy and traveller communities) might find AI services much harder to use, leading to greater inequalities.

While there are a considerable number of studies exploring the overall perceived acceptability of, and trust of AI technologies in healthcare by healthcare professionals and the public, there is significantly less information about demographic differences in attitudes. Furthermore, there is a lack of large-scale trials of AI in healthcare settings, and even fewer trials which look at sub-group differences in experiences and outcomes of AI assisted healthcare. Robust research data based on well designed, large-scale trials is a key piece of information healthcare professionals would like to see in order to enhance their trust in AI.

On balance, there is insufficient evidence so far to determine whether AI will impact positively or negatively on health inequalities, it is likely that it will do both. An significant takeaway is the importance of working with different groups to design and build AI that works in an inclusive way, meeting the needs of different people and tailorable to their requirements. It is also important to recognise what an AI model has not been trained to do, and ensure that AI is not accidentally misused, leading to poor outcomes and undermining trust.

2 AI in healthcare

There are a lot of different definitions of Artificial Intelligence (AI) explored in Section 5 below. For this report we have used the broad definition that AI refer to the ability of a machine to display human-like capabilities such as reasoning, learning, planning and creativity[1]. This chapter explores how AI can be used in a healthcare context, how healthcare professionals, patients and the public feel about AI and the opportunities and risks of using AI in a healthcare setting.

2.1 What are the opportunities for AI in healthcare?

In 2019, the NHS X paper, "Artificial Intelligence: How to get it right" [2] set out five areas of care where automation could make a difference:

- Diagnostics including image recognition
- Knowledge generation such as pattern recognition
- Public health including digital epidemiology and national screening programmes
- System efficiency such as optimisation of care pathways
- P4 medicines (predictive, preventative, personalised, participatory) including advice and treatments

Overall, professional and patient attitudes to the use of AI in healthcare are broadly positive, as long as certain safeguards are in place[3]. According to a recent large-scale quantitative study[1] by Health Foundation "over half of the UK public (54%) and three-quarters of NHS staff surveyed (76%) said they support the use of AI for patient care, and an even greater proportion said they support the use of AI for administrative purposes (61% of the public and 81% of NHS staff surveyed)"[4].

However, support varies depending on the specific use of the technology, with people feeling more comfortable when the AI was supporting a clinician rather than replacing them[5]. Typically, people who were more confident or who had experience using AI were more likely to be positive about its use in healthcare[6], [7]. The literature regularly identifies lack of education, knowledge and guidelines about AI as a key barrier to trust and usage[3] [8] [9], [10].

2.1.1 Healthcare professional views on the role of AI

Healthcare professionals' views are important for two reasons: firstly, because they will be the people using AI tools or delegating tasks to AI but also because patients and the public will be looking to clinicians for reassurance, and will still expect to be able to hold someone to account if AI makes a wrong decision[11]. Limited academic studies were found that explored the views of British healthcare professionals. However, a recent survey by the Health Foundation of 1,200 NHS staff found that among the occupational groups surveyed, doctors and dentists, allied health professionals and those in scientific and technical roles were more likely to be looking forward to using AI as part of their role. Nurses and midwives, those in administrative and clerical roles and those in other clinical services (such as health care assistants and health care support workers) were less likely to agree[4]. In a number of cases, the perceived lack of proven clinical benefits led authors to conclude more research is needed in order to build professional's trust in AI[12], [13].

[1] Fieldwork conducted in June and July 2024. Included 7,201 nationally representative members of the public (aged 16 years and older) and 1,292 NHS staff members.

Most healthcare professionals express confidence that AI will not reduce the need for clinical training in the short to medium term, although some express concerns that increased reliance on AI could lead to people becoming de-skilled. In an earlier publication[14], The Health Foundation surveyed NHS staff to identify the 'biggest opportunities' for AI improving healthcare. Out of the options presented, 'analysis of images and test results' was ranked highest (picked by 40% of participants), while 'risk prediction and screening', 'use of robots in surgery' and 'demand and capacity management' were all chosen by 28% of participants. Only 2% of respondents thought 'robotic carers and assistants' represented one of the three biggest opportunities.

2.1.2 Patient and public views on the role of AI

The Centre for Data Ethics and Innovation (CDEI) started a public awareness tracker in 2021 and wave 4 was recently published[15]. Over this time, public awareness of AI has been increasing rapidly, but while over seven in ten of the UK public now say they can explain the term to some extent, deeper knowledge remains mixed. More people have now tried using AI including chatbots: six in ten members of the public report having used an AI chatbot in the past three months, with over four in ten of these using them at least once a month. Familiarity varies across demographics groups, with younger people, those of higher socioeconomic status, and London residents reporting higher levels of familiarity. This is important as in other studies, familiarity leads to a higher level of trust and willingness to use the technology.

The CDEI research[15] also consistently shows that most of the public trust the NHS to act in people's best interests, being trusted by 80% of those who are digitally disengaged (200 people interviewed by telephone) and 85% of the online sample (4,947 people interviewed online inclusive of the following boosts: Wales = 50; Scotland = 511; Northern Ireland = 530). People remain more confident in the NHS than other public sector bodies handling their data, but confidence has declined, especially among those aged 35-54 and 55+, as well as within the higher socio-economic grades (ABC1) which CDEI attributes at least in part to awareness of recent data breaches. One of the main concerns about AI relates to data security, and some population groups are more concerned about this than others.

In a recent survey for Health Foundation of 7,201 nationally representative members of the public (aged 16 years and older)[4], over half of the UK public (54%) said they support the use of AI for patient care, and an even greater proportion said they support the use of AI for administrative purposes (61%). Among the public, young people (aged 16–24 years) are less likely to believe that AI will improve care quality compared to other age groups, and women are less likely to believe that AI will improve care quality compared to men.

The same survey shows that, from a list of possible uses, administration tasks such as using AI to create letters or recording appointments have most support (net positive 39 percentage points and 36 percentage points respectively) although even for these relatively popular uses, there is significantly less support if the AI is not supervised. Other studies show that the UK public will accept the involvement of AI in the diagnostic process, if it is perceived to have advantages (e.g. speed up process, more effective) as long as humans remain involved in the decision-making process[16], [17].

A survey of Diabetes UK members found that previous use of chatbots was the main predictor of use of a medical chatbot. However, it also showed that respondents (mainly women aged 55 plus) did not trust chatbots to provide a diagnosis or medical advice, while they were more open to engaging on topics such as sleep or nutrition. Participants also expressed a preference for voice-based interaction rather than typing[18].

2.2 What are the perceived risks and barriers?

There is broad agreement on the perceived risks of use of AI in healthcare, although different stakeholders can weigh the risks differently. The main risks identified are lack of trust and confidence, concerns about privacy and data security and questions about bias. Many of these risks relate to, or could exacerbate, health inequalities.

2.2.1 Lack of trust and confidence

The first barrier to use of AI, often mentioned, is lack of trust or confidence in the technology. Health Education England[19] note that that trust and confidence are often used interchangeably, but perceive trust to be a binary concept while confidence is more nuanced and potentially more helpful. Their 2023 report *"Understanding healthcare workers' confidence in artificial intelligence"* states that the aim should be to develop an appropriate level of confidence in different AI, rather than always seeing trust as the ultimate goal.

There are different frameworks for building trustworthy AI that are likely to contribute to building confidence, and consequently to increasing acceptance. Typically they include ways to address the other risks listed in this chapter, as to build confidence (and be trustworthy) AI has to overcome all these risks and meet expectations at every stage of the AI's development, from business planning through to deployment[20]. For example, the AI Trust, Risk and Security Management (TRiSM) sets out four pillars of trust: Explainability, ModelOps (risk management integration in AI model), AI Application Security and Privacy[21].

Another lens to consider is technology acceptance and adoption, with studies showing that even if healthcare professionals claim not to trust AI, it can nonetheless influence their decision-making by making a recommendation if they use it[22]. The Technology Acceptance Model (TAM) proposes two underlying requirements for acceptance – perceived usefulness and ease of use [23], and in medical cases, technology is likely to be considered useful only if it is considered trustworthy[24]. The Unified theory of acceptance and use of technology (UTAUT) builds on TAM and a number of other theories, and concludes performance and effort expectancy are important, alongside social influence and facilitating factors. It also notes that moderating factors (gender, age, experience and voluntariness of use) are important considerations[25].

Often lack of transparency (the 'black box') is perceived to be a significant barrier, making it hard for clinicians to understand how the AI reached a conclusion, and therefore assess its veracity. However, due to the way that AI works, it is not necessarily straightforward for it to demonstrate how it reached a conclusion[26]. There can be a tension between reliability and explainability, and typically patients and the public would choose reliability if required to choose between the two[27], whereas studies show health professionals feel that AI must be able to explain how it reached a conclusion in order for the human in the loop to assess and trust the AI output[11], [28].

As outlined above, both patients and the public feel it is important to keep a human 'in the loop', but different humans will use AI in different ways. For example, considering an AI that helps interpret x-rays, a generalist, such as emergency department clinicians who read x-rays alongside other tasks, may be more likely to trust the AI recommendation, while specialists, such as radiologists who read x-rays every day can be more circumspect. Years of experience and attitudes toward AI can also impact, with people with less experience or who are more positive about AI being more likely to be willing to accept its recommendation. Consequently, there is a risk that those with less experience or knowledge are more likely to make errors by incorrectly following AI advice[22].

An approach which is seen to improve trust and confidence is involving stakeholders in the AI development[29]. Doing so can help clarify expectations and concerns and address them early on. Additionally, ensuring that there is an option to evaluate AI outputs and provide feedback is important to ensure it continues to improve. In addition to involving clinicians as stakeholders, it can also be of value to include patients themselves, including people from minority groups, to ensure that they do not become more marginalised through the design and delivery of an AI tool[30].

2.2.2 Other risks and barriers

As outlined above, a key element of trust and confidence is addressing the known risks of AI. Specifically:

- Privacy and data security
- Bias
- Impact on profession
- Legal
- Other ethical concerns

Privacy and data security

Privacy and data security are a key concern for both patients and their clinicians[31], [32]. These concerns include the risks of patient data being hacked or leaked, but also the use of data for unwarranted commercial purposes[11].

Some demographic groups are more concerned about this risk than others, potentially meaning they could be more likely to decline AI involvement in their healthcare, but also meaning they could be missing from training data (see **Bias** below). Specifically, historically marginalised communities often experience mistrust and reluctance toward research engagement due to past exploitation[33]. Where information is considered particularly sensitive, for example, disability, sexuality and mental health data, people have a greater need and expectation of data privacy and security[34]. This is the case for a lot of the data required to minimise health inequalities.

A 2021 study of NHS outpatients found that people with lower education levels and those who did not own a smartphone were less likely to allow their anonymised data to be used by the NHS and university researchers. Equally, participants who were not white were significantly less likely to share their data. The younger people surveyed (under 45 years old) were less supportive of the use of machine learning in diagnostics and imaging[35].

Bias

Bias is an important concern and is the main way that the use of AI could increase health inequalities. A well-known example is the American insurance algorithm that prioritised white patients over black patients for extra care support, because it used previous health costs as a proxy for future need, and so high acuity in Black patients was missed because they were less likely to use healthcare[36]. Similarly, dermatologists and GPs are concerned that a bias towards lighter skin types among algorithm training data that could potentially cause health inequalities based on skin type[37].

Overall, health professionals express concern that unrepresentative historical datasets used for training AI could lead to biases in outcomes[11]. Underrepresented groups extend beyond racial and ethnic minority groups, including certain socioeconomic or gender groups, or individuals with disabilities[33]. For example, a tool using AI in intensive-care-mortality prediction, was shown to be more accurate for white men compared with women and patients of minority ethnicities[38]. Similarly, studies have shown that AI trained predominantly on adult data might not be appropriate for children and vice versa[39]. Concerns have been raised that there might also be digital ageism in AI that means it also does not serve old adults well[40], and that an over-medicalised view of disability can also introduce bias[41].

A further consideration is that NHS coding of demographic information, specifically race, is not consistent and therefore has the potential to introduce error into both the training data and the patient's individual record which could inform an AI response. Recent work by the Office for National Statistics has demonstrated that of those recorded as White British in health admin data sources, more than 96% reported the same ethnicity in the National Census. However for Black and mixed ethnicity records the level of congruence was significantly lower[42]. Missing or incorrect data might also apply for other demographic information, including disability[41].

There are also questions about whether and how AI-based tools can pick up on variations in cultural norms such as discussions about culturally-appropriate behaviour, differences in verbal/nonverbal expressions, and pronunciation or whether they capture important culture-specific information related to empathy or cultural practices[43].

Biases also exist in translation and voice activated AI services. The English language is favoured over other languages, and this can result in nuance being lost in translation. However, not all English speakers have the same experiences: those with strong accents and women can potentially find it harder to interact with a voice-operated AI (see section 2.4 below)[44].

Impact on profession

As outlined above, most health and care professionals do not feel that AI will replace them, they do believe, however, that their jobs are likely to change. The two main concerns that stem from this are skill loss, because the profession becomes more reliant on AI over time[45], and the impact AI could have on patient-centred care, especially if it reduces time spent with patients[46].

The main functions that patients and clinicians believe human oversight of AI should deliver are to:

- sense-check decisions to help mitigate bias and reduce mistakes,
- ensure that the clinician-patient relationship is preserved[4], and
- ensure that care is compassionate and empathetic[3].

However, although lack of compassion and empathy is often raised as a concern, especially for delivering difficult news, there is emerging evidence that AI technologies can mimic elements of compassion, or to enhance the compassion in a healthcare system[47], [48]. Nonetheless, other research shows that there is still a gap between empathy people feel for stories written by humans or AI, even in blind trials[49].

Another recurring barrier is the perceived usability of the AI. Healthcare professionals express concerns that AI could add to their workload (and burnout) rather than making them more efficient or effective[50]. Technology that is hard to use could both impact on the quality of patient care, and the time available for this. Health Education England (now part of NHS England) noted that there could be a considerable skills gap when introducing AI to the workplace and committed to developing strategies to address this[51].

For healthcare professionals to be willing to use AI they may need assurance that it will not create more work for them because patients have difficulty using it. Best practice in working with people with different disabilities or from different communities is to work collaboratively with the individual, rather than adopting a paternalistic approach. It is not clear whether AI will be shaped by people with different users, in order to ensure it meets their needs, or will provide the customisable options required to make it accessible for a wide range of different people[52], [53]. Alongside physical accessibility requirements, there are also linguistic and cultural differences that AI will ideally respond to[53]. While it is anticipated that a healthcare professional would listen and adapt when speaking to a patient, AI would need to be programmed to ensure it is included.

Legal

Legal concerns mainly relate to accountability: specifically, who should be held to account if the AI leads to a suboptimal outcome for the patient. There is a particular risk for clinicians that when the AI advice is correct and the clinician follows it, the AI will get the credit, whereas if it is incorrect and the clinician follows it then the patient or their family will want a human to blame. A study of use of robotics in surgery demonstrated that older, less educated patients were more likely to expect doctors, rather than the robot manufacturer, to be accountable for malfunctions[54].

Differentiating between accountability, liability, and culpability may be helpful for mitigating this risk, noting that the conclusion could be different for different AI functions[31]. Currently, the UK Information Commissioner's Office guidance states:

"There should be no loss of accountability when a decision is made with the help of, or by, an AI system, rather than solely by a human. Where an individual would expect an explanation from a human, they should instead expect an explanation from those accountable for an AI system."[55]

This is helpful but may not necessarily clarify who is accountable if a healthcare professional decides to override the decision of the AI, or reviews the decision of the AI and decides to follow it but had the option not to.

People place value on keeping a human in the loop because they are hopeful it will help identify errors. However, humans are also fallible, and some studies suggest that seeing an incorrect diagnosis from an AI might make the human *more* likely to make an error[56]. Even where using explainable AI (XAI), ensuring the ability to understand and traceback decisions was not sufficient for avoiding incorrect decisions, although less errors were made than when the AI decision was not explained at all[57].

There are also legal issues related to data privacy and security, including assurance that the AI was trained on an appropriate dataset and that it processes data in line with the relevant regulations (in England the UK GDPR and DPA)[58]. Additionally, health and care organisations in England are expected to uphold the Caldicott principles for data use[59].

In England there is work underway[60] in key organisations including Care Quality Commission (CQC), Health Research Authority (HRA), Medicines and Healthcare products Regulatory Agency (MHRA) and National Institute for Health and Care Excellence (NICE) to ensure appropriate regulation is in place for AI used in healthcare. However, international collaboration and coordination on AI governance for healthcare would be valuable to ensure coherent solutions are developed worldwide[61].

Other ethical concerns

For those who believe AI will improve healthcare outcomes, there is a concern that unequal access to AI services could be an ethical concern[62]. This could occur both at the establishment level, with some health and care organisations able to afford more and better AI solutions, which can both directly benefit patients, but also indirectly benefit them because it can take burden off health and care professionals, reducing burnout and enabling them to spend more quality time with patients.

Additionally, it could happen at the individual level, if individual patients do not have the technology, internet connection or skills to access AI healthcare. For example, a study showed that when patients were given a tablet in a hospital setting to help manage their condition, not all patients benefitted equally, with younger, white patients making the most use of the tool[63]. It is important that initial training is provided so that people know how to use the technology, and for follow-up support to be available[52].

The cost of implementing AI systems is also identified as a barrier to uptake[11]. Outside the UK, the cost is perceived to risk increasing health inequalities as only some patients will be able to afford AI supported healthcare. In the UK the tension may be what to prioritise within a given budget. Additionally, there is a risk that using AI in prevention or early diagnosis could overwhelm other parts of the system[64]. People working in AI note that the motivation behind the developers might not necessarily align with patient expectations – for example, it could prioritise operational efficiency above individual patient outcomes[65].

2.3 Some lessons from real life

The following case studies explore implementation of AI in real-life settings and capture the key learnings. The main issues faced during roll-out largely reflect the barriers above:

- Technology did not fit with workflow / existing routines / added to perceived workload / difficult to use / perceived to be unreliable[64], [66], [67]
- Insufficient IT infrastructure (insufficient connectivity, lack of computers) and IT support locally[64], [66], [68]
- Concerns about patient data privacy and governance (patients required reassurance, professionals not able to give it), and issues with informed consent where patients have reduced capacity[64] [66]

Some additional issues included:

- No clear governance to decide whether or not to procure AI, which AI to procure or what outcomes were desired, which includes staff input[66]
- Lack of transparency / inability to discuss / reason with the AI as would with a colleague if views differ, and importance of ability to override (especially for experienced staff)[56]
- Unhelpful if degree of certainty not provided - if AI just presents a single answer and no qualifier estimating the level of certainty then the user may erroneously assume the AI is 100% confident in the answer[56]
- Difficulties finding time for preventative technology in services focussed on crises[66]

- People most likely to benefit from remote monitoring were least likely to be compliant with using the technology as required[66]
- Patient frustration with having to repeat answers when talking to chatbot (due to limited vocabulary, voice recognition accuracy, or error management of word inputs)[69]

Some of the deployments were considered successful, typically those used by patients as part of condition management or understanding risk[68], [70], [71], [72], [73] and advice includes:

- Use an iterative development process with end users (patients and/or staff) to ensure high user satisfaction[66], [70], [74]
- Need for engaging workforce training, and clarity on when the AI is appropriate to use[66], [74], [75]

However, a review of studies of AI conversational agents in healthcare concluded that although the studies generally reported positive outcomes relating to the agents' usability and effectiveness, the quality of the evidence was not sufficient to provide strong evidence to support these claims[69]. This review also found there is very limited discussion of differences in experiences or outcomes for different groups, and consequently limited consideration of the potential impact on health inequalities. This absence of differentiation between different user groups may be due to a perceived lack of relevance: a small-scale survey of professionals, designed to identify which factors impact trust and acceptance of AI in medicine concluded that, while knowledge and attitudes of clinicians and patients were relevant, age, gender and education were considered to be of low relevance when trying to anticipate who is likely to trust AI[76].

2.4 AI and languages

2.4.1 AI and translation

Outside of the health literature, different studies have explored how well AI can translate and provide voice services in different languages, dialects and accents. Overall, the quality of written translation is considered to be broadly acceptable, especially in languages that commonly occur online and therefore in training data sets, although slightly less good than human translation[77]. There is a lack of evidence on the adoption and/or maximisation of AI and machine learning (ML) as possible solutions for the hearing impaired[78].

According to a recent article[79], English, followed by Mandarin Chinese, Arabic and French are the languages that are most common online, followed by German, Portuguese, Spanish and Finnish. The article claims these languages have large and accessible collections of digital text and transcribed recorded speech. Issues arise for other languages, not least because AI is already being used to create translations of them, and therefore creating the translations that other AI models get trained on, rather than having humans involved in the translation. The article concludes that translation Large Language Models (a type of AI) "fail resoundingly in many languages such as Swahili, Bengali, Urdu or Thai". However, another study has shown that while AI translations of health research abstracts were considered acceptable from English to Chinese, German, Italian and Japanese, the French translation was considered much less successful[80].

2.4.2 Literacy

Developers can choose whether the interface with AI is text or voice-based. Low literacy correlates with a number of groups who are known to experience health inequalities. For example, in England[81], older people have lower literacy, as do the unemployed, permanently disabled and people from Asian and Black ethnic backgrounds. The same data shows people with mixed race have higher literacy scores than White people. Consequently, it might be reasonable to assume that a voice-based AI would help make healthcare more accessible for some groups.

2.4.3 Voice activated AI

While voice activated AI may be a good solution to low literacy, or potentially user concerns about usability, it works better for some voices than others.

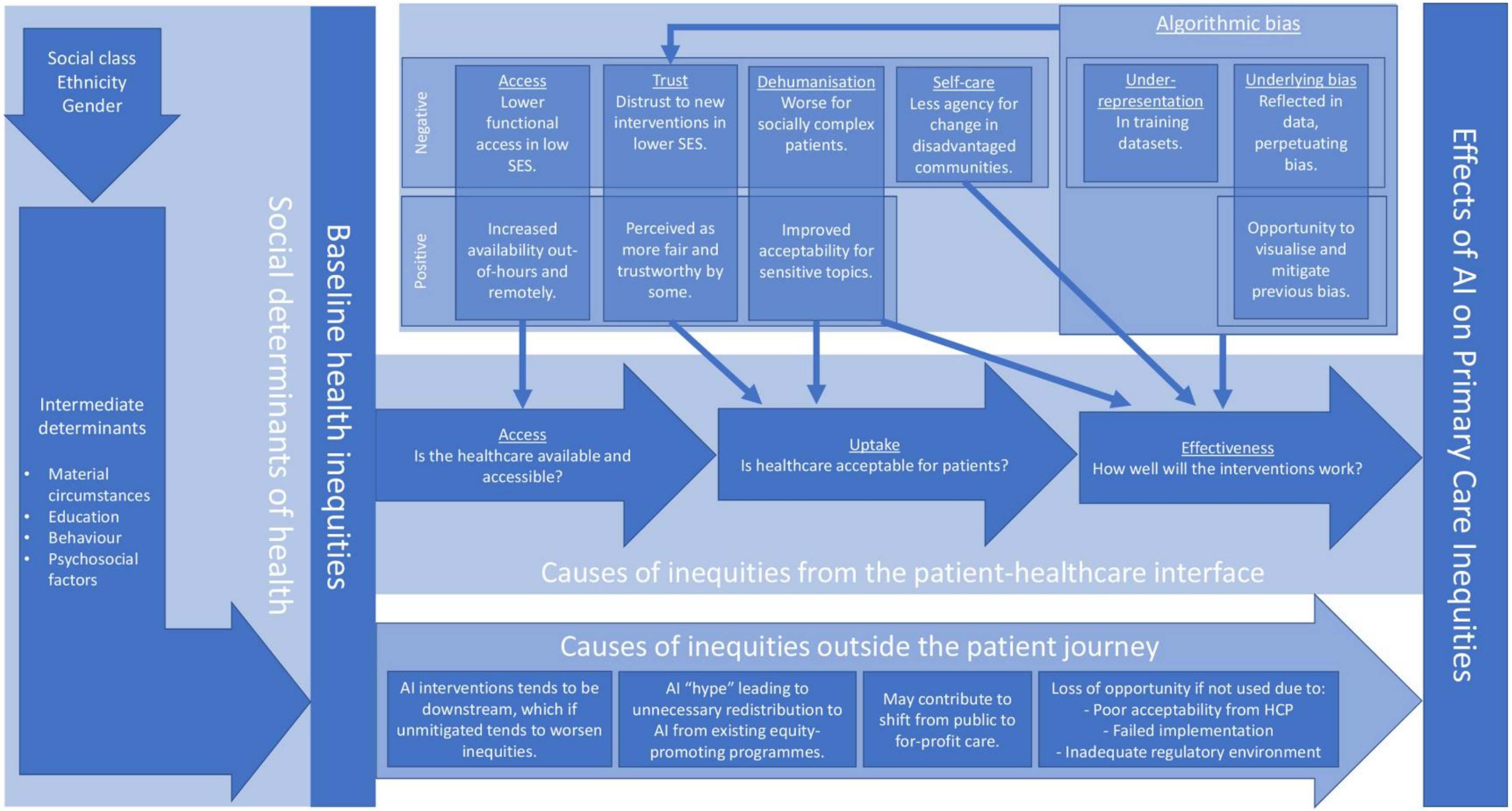
There is evidence that AI voice recognition does not work equally well for all voices. An American study which looked at five automatic voice recognition systems (developed by Amazon, Apple, Google, IBM, and Microsoft) found all five had a higher average word error rate (nearly double) for Black voices than White voices, even if they were reading from the same script[82]. A UK study[44] found that women and speakers from Scotland were least accurately transcribed by AI, other studies have also found regional differences in accent recognition.

Chatbots can also struggle when an individual switches between different languages, as is common for some multilingual cultures such as Indian people who might switch between English, Hindi and another minority language. There can also be specific difficulties when users try to transliterate between languages (e.g. spelling a Hindi name in English)[83].

3 AI and inequalities

As outlined above, many of the perceived risks and barriers to using AI have the potential to exacerbate health inequalities. A recent scoping review[84] found that *"research on how AI may affect HI in primary care is limited, and is largely confined to either observations around accessibility or concerns over biased algorithms"* and that *"there is a further need to specifically study discrimination by specific* characteristics, also including wider ranges of marginalised populations" which aligns with the outcome of this review. The result of this review was the figure below (Figure One). The review also concludes that it is important to note that not all health inequalities occur within the patient journey, and consequently highlights the importance of considering the whole system when considering how to address health inequalities.

Figure 1: Conceptual framework for how AI could affect inequalities in primary care, created by: A. d'Elia *et al*[84]



This chapter looks at the use of AI from the patient perspective, and how it could impact on healthcare access, experiences and outcomes.

3.1 Access

3.1.1 Risks and barriers

The first consideration is around the impact of the use of AI on access to healthcare services. There are a number of barriers, and it is possible that they are interconnected. Considering the COM-B model for behaviour change[85], in order for a change in Behaviour (in this case use of AI) patients will need to have the Capacity (i.e. the skills to access), Opportunity (i.e. the technology needed to access), and the Motivation (i.e. the desire to access).

While Opportunity barriers will be lower if the AI is used within a healthcare environment and if it utilises NHS provided technology or basic technology available in most homes, patient Capacity and Motivation may still be absent unless healthcare workers actively intervene. If the intention is for the patient to use the AI directly then it will be important to ensure that all patients have the Opportunity (i.e. access to the relevant technology), in addition to Capacity and Motivation.

Opportunity

If use of an AI tool requires broadband, this is now widespread and superfast connections are available to 98% of households in England, with only 0.1% of properties unable to get decent broadband[86]. However, full-fibre coverage continues to vary between urban and rural areas, with 99% of urban residential premises having access to superfast, compared to 90% of rural residential premises[86].

While the connections are available, not all households install them. In 2023, Ofcom found that 95% of households had access to the internet at home. Not having access was most common among those aged 65-74 (10%), over-75s (29%) and those living in a low social grade (DE) household (12%)[87].

Some communities, including homeless people may not have any access to the internet, or may only connect via public Wi-Fi which is generally not secure or private. As such they can express concerns about sharing health information digitally. Gypsy and traveller communities often do not have digital access, or use the internet in a narrow way to stay in contact with family and friends, but do not necessarily have the skills or literacy to use digital healthcare[88].

Capacity

If the technology is in place, inequalities can also arise from the ability to use the technology. For example, just over half (54%) of the UK population say they have used voice controls (smart speakers, voice control in car / on phone), but this is significantly lower for those over 55 years (43%) or over 65 years (35%). Low income households (under £10.4k) are significantly less likely to use voice controls (40%)[89]. This data is not published with details of ethnicity, but other studies have shown that ethnic minority patients in England encounter more difficulties with digital health services than the white majority[90]. Studies outside the UK show that women might be more digitally excluded than men, and in some cultures may have to request permission to use technologies[91].

While a well-designed user-interface could make interacting with the AI very straightforward, there is likely to be a reason why people have chosen not to use technology so it might take significant persuasion to get them to try. As outlined above, providing a tablet to access an AI service results in differential uptake, suggesting that having capacity and motivation are important[63]. A review suggests limited high quality research into the use of telemedicine, and flags the need to know more about cognition, perception, and behaviour of older patients[92].

Motivation

A further barrier to access is trust. This may impact both willingness to use the AI, and also willingness for data to be used to develop the AI. Study findings are inconsistent: for example, some find women more likely to trust AI than men and others vice versa. This inconsistency can potentially be attributed to the fact that AI is still a relatively new technology and therefore people will be somewhat reliant on previous experiences of AI, and of healthcare, alongside the information provided in the survey itself to form a judgement[93].

Typically, openness to AI use in healthcare appears to decrease with age[71], [94]. There may be differences by nationality, with the same EU study showing the most receptive countries were Romania and Spain with almost 80% approval, while in France fewer than 50% of participants declared approval of AI[95]. Some studies have shown that aversion to AI involvement is higher among people with less education, or from lower social classes[96], [97]. Some studies suggest that cultural and socio-economic differences, including low health literacy, and cultural and religious beliefs or distrust in government might also make people less open to using AI[53].

A German study demonstrates that different groups of people value different features of AI. For example, older and less educated people were likely to prioritise having a 'human in the loop', while young and well-educated participants were more likely to value an emphasis on the AI's ethical principles. Other groups were more concerned about the 'fairness' or 'safety' of the technology[98].

Privacy, data security and consent

Many people who experience health inequalities are in minority groups. Therefore, depending on how a training dataset has been developed, they are theoretically at higher risk of being re-identifiable from de-identified data. There is also a potentially higher risk if their data is reidentified – particularly if it contains sensitive details such as information about sexuality, mental health records, criminal record or refugee/asylum information. Consequently, this information may be missing from records[34] or individuals may choose not to be included in a dataset if given a choice[99].

Finally, ethics processes can require informed consent for trials of AI. Where informed consent is required, it is possible that some groups may be missing from data or trials, including those who may not have capacity to consent or whose consent it would be harder to capture. This can impact on adults with learning difficulties or dementia, disabilities[100] and also children and young people considered too young to provide informed consent[39].

3.1.2 Opportunities

Unlike traditional health services, it is possible that AI services such as chatbots can be available 24-7 and from any location. As such, people might find them easier to access and use, and as such they could increase access and use[84]. Some studies suggest that younger people (aged up to 45) are generally more likely to be positive about the use of AI in health, for example as an assistant to support mental health[101], [102].

AI could be particularly beneficial for young people experiencing social anxiety, and could remove a key barrier to seeking help by providing anonymity and enabling them to avoid the perceived stigma of seeking help for their mental health or sexual health[102], [103]. Similarly, some studies suggest that telepsychiatry might enhance access to mental health services for ethnic minorities, as long as it is supported with a culturally competent workforce, and appropriate education and training[53].

For refugees and asylum seekers, lack of language skills and difficulties accessing traditional mental health services for both physical and emotional reasons (shyness, embarrassment, fear, shame) can be a barrier to accessing care. Therefore, using AI can potentially provide improved access to mental health support[104].

3.2 Experience

3.2.1 Risks and barriers

The experience of AI being used in healthcare is likely to be shaped by the healthcare professional that introduces it. The NHS is one of the UK's most trusted institutions[105], and doctors and nurses are among the most trusted professions[106]. As such, if the healthcare professional trusts and endorses the use of AI then it is more likely that the patient will accept its use[64]. It will therefore be important for healthcare professionals to be trained and educated in the use and benefits of AI, so that they can share this with patients[107]. Trust can easily be lost so it is important that healthcare professionals use AI appropriately, and for the intended purposes only, in order to ensure that trust is maintained.

Literacy may also be an issue when using AI: 18% of people in England have very poor literacy skills[108]. Again, this low literacy is not spread equally across the population, but as outlined above (section 2.4.2) it is found more in specific groups including older people, unemployed, permanently disabled and people from Black and Asian backgrounds. Directly translated materials may also not help, where the translated terms are overly medical and might not be understood[109]. For these groups, voice activated technologies might be easier to use, but, as noted above (section 2.4.3), they can be less helpful when people have a strong accent. Inadequate translation can cause miscommunication or misinterpretation of culturally informed narratives, and several authors suggest it is not yet appropriate to replace face to face translators with AI, especially for complex cases[53], [110].

A review[100] demonstrated that there is a lack of use of the social model of disability in AI research. The social model focuses on the societal and environmental obstacles that disable individuals rather than solely attributing disability to an impairment. This means that people's experiences of using AI might be made unnecessarily difficult, because their needs have not been considered. Lack of user involvement is considered to exacerbate this issue[111].

Finally, there are existing disparities in how well certain groups respond to self-care directions. It is therefore possible that increased use of AI which encourages self-care could increase inequalities, because some groups will be better placed to follow the instructions than others[84].

3.2.2 Opportunities

While it is possible that concerns about algorithmic bias may lead to lower levels of trust, it is also possible that, by apparently removing human decision-making from the process, some people may choose to trust AI more than a human[84]. Equally, while most people express a preference of interacting with another human, for some it might be more comfortable or easy to 'talk' to AI[84]. Some young people describe AI as potentially 'less judgemental', making it easier to work with when talking about sensitive issues such as mental health[102].

As noted above, there is a risk that AI adopts cultural norms from a particular group, and is not sensitive to cultural differences[53]. The same might be true of medical professionals, especially when treating patients from different backgrounds. Therefore, AI has the potential to be a tool to reduce inequality by identifying these differences and helping the clinician to adapt, rather than simply enabling a translation which might be linguistically correct, but which could miss cultural context important to the patient experience.

3.3 Outcomes

There are already significant differences in outcomes between different groups in the population, which is why considering health inequalities is important. For example, maternal deaths are 3.7 times more likely for Black women compared with White women giving birth in the UK[112]. Therefore, if AI replicates current outcomes then health inequalities may persist.

3.3.1 Risks and barriers

There is limited data on the impact of AI use in healthcare on outcomes for people in different health inequality groups. Currently the data being used to train AI may not necessarily be representative of the UK population, or may include insufficient data on smaller sub-groups. As discussed above (section 2.2.2), the bias in the training sets means that the AI outputs might not be equally appropriate for all patients. Studies have shown that it is necessarily not appropriate to utilise AI trained on data from different countries, as there are other variables which will impact how data should be interpreted.

There is a risk that AI might focus too closely on medical factors, while overlooking psychosocial factors which may also be relevant[84]. The body of work on the social determinants of health recognises that a whole range of factors such as employment, housing, disability and education can impact on health outcomes[113] and this information may not be available to AI[34]. While it is possible that the medical professional might ask for this information in a consultation it might not be coded or available in a medical record.

Although evidence suggests that technology-based mental health interventions might support better access for refugees and asylum seekers, currently there is limited evidence that this support is effective in reducing symptoms of depression, anxiety or PTSD[114].

3.3.2 Opportunities

Reviews such as The Maternal, Newborn and Infant Clinical Outcome Review Programme suggest that some of the improvements to be made include ensuring healthcare professionals have the training and knowledge they need to mitigate risks (such as symptom awareness)[112]. Well-designed AI support could provide these prompts, helping to ensure the right questions are asked and appropriate monitoring is put in place.

There are a number of examples of AI being used to support rehabilitation for both children and adults. Currently the evidence from these is mixed, but there is potential for AI to improve outcomes for people with physical disabilities, such as those developed after a stroke[115]. Similarly, there are examples of robotics and other AI being used in rehabilitation for children, although typically these studies only consider age and disability, and do not consider other demographic factors which might also be valuable to understanding the outcomes of using the technology for different users[116].

A study in Saudi Arabia using ChatGPT to provide support for anxiety disorders found that younger people, women and people living in urban areas were more likely to rate the service positively for trustworthiness and effectiveness[117].

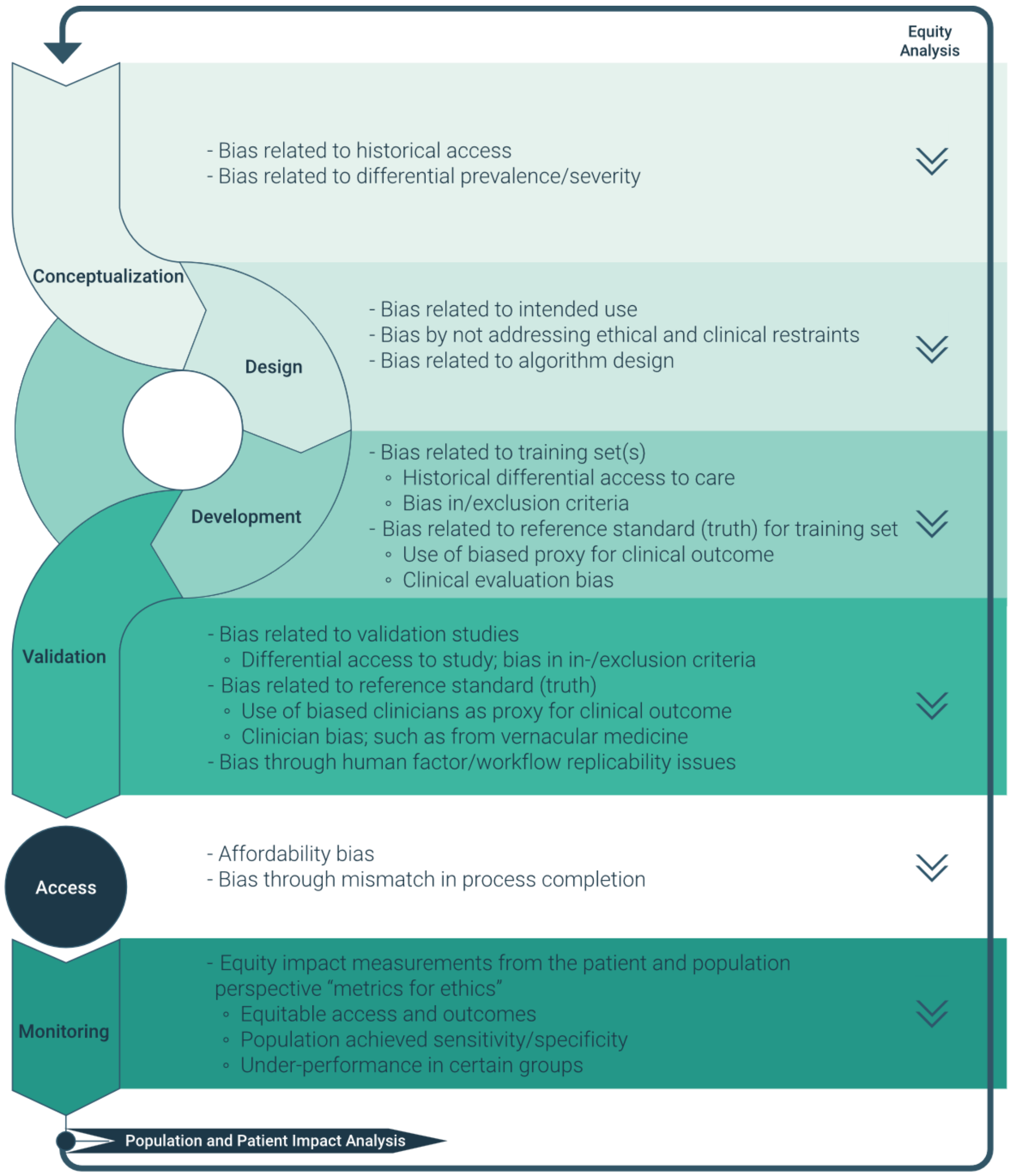
3.4 Identifying and addressing inequalities

There are a number of proposed measures that could help identify and address inequalities arising from the use of AI in healthcare:

- Lack of AI education is a significant barrier, as the healthcare community and the public at large both have a limited understanding of how AI can be incorporated into practice[118].
- Selecting the appropriate algorithms for supporting decisions and training of decision makers to understand and scrutinise the outputs of algorithms are key factors in increasing accountability and transparency[57].
- Diagnosability, a novel autonomous AI metric, may help evaluate equity by calculating the ratio between the number of valid versus indeterminate results for a specific population. Low diagnosability values in a subgroup may denote a lack of equity. To support such post-hoc equity metrics, AI researchers should maintain statistics and regularly monitor demographics, including vulnerable and protected groups[118].
- Apply formal statistical methods to evaluate data quality and reliability of AI models and data imputation techniques to account for missing data with awareness of potential biases and inaccuracies introduced[33].

M.D. Abràmoff et al.[119] propose that in order to successfully mitigate the risk of AI increasing inequality, it is important to consider bias that can be introduced throughout the Total Product Lifecyle (see diagram below). Specifically, they set out different biases that can be introduced (or mitigated) from the conception and design of AI, through to the development and validation and also the access/marketing and finally the monitoring. Others advocate for the involvement of specific communities throughout development, to ensure that the AI is culturally appropriate, physically accessible and meets their different needs[53].

Figure 2: Total Product LifeCycle (TPLC) equity expanded framework with examples Source: M.D. Abràmoff et al.[119]



Ultimately, many authors emphasise the importance of using AI as intended and only in the specific circumstances it is trained for. The risk of misuse is that it will give misleading answers, and in turn this could reduce trust. It could also push new technology to uncontrolled consumer products such as smartphone apps, leaving the traditional health system unable to manage increased health anxiety and care-seeking[84].

4 Inequality groups

This chapter uses the same information as the previous chapter (Chapter 3) but reviews the impact of AI in healthcare on different groups of people. Note that throughout the literature there was very little evidence about the impact of AI use on healthcare outcomes. Throughout the chapter there are cross references to the previous chapters in brackets.

Although it is known that AI models can become less reliable for groups not well represented in the training data (2.2.2), and that there can be framing effects meaning less experienced or specialist doctors may tend to follow the AI advice (2.2.1), there are not the empirical trials to evidence the extent to which this impacts on patient outcomes.

By definition, being a member of these groups can be sensitive data, and as such data privacy and security is likely to be particularly important, especially relating to race, religion, health, sexual orientation, mental illness and criminal justice[120].

Finally, while this chapter breaks down findings by specific characteristics, intersectionality is often an important consideration, where one person has several characteristics which might impact their experiences of AI. There is a balance to strike between making AI inclusive and ensuring that it feels relevant to specific groups who might otherwise assume that it is not designed for them to use.

4.1 Age

There is mixed evidence on the use of AI in healthcare for different age groups, although some suggest it will be most quickly adopted among young to middle-aged adults (3.1.2).

There is some evidence that access is likely to be harder for older people who might have less familiarity with the required technology (3.1.2). They might also have lower levels of trust, and a higher expectation of having a human in the loop (3.1.1). As people get older, they may have physical reasons (e.g. dexterity) why they may have difficulties operating technology such as a smartphone. There is also a risk that healthy older people might not be as well represented in datasets, thus leading to bias (2.2.2).

Similarly, children and young people may not present in the same way as adults, and therefore it will be important that any AI is trained on an appropriate dataset (2.2.2). Generally, younger people are likely to find the technology easier to use, and some may prefer it to interacting with a human: especially on a topic considered to be embarrassing or where there could be stigma attached (3.1.2). There is some evidence of AI being developed for use in rehabilitation and physiotherapy for children[121].

Generally, the attitudinal research suggests that younger people are not as likely to believe that AI will have an impact on healthcare, but this does not necessarily mean they will be averse to its use (2.1.2).

4.2 Sex

There is not consistent evidence about how sex could affect the impact of AI in healthcare. Some studies show that women are more positive and trusting of AI, while others suggest the opposite (2.1.2). It is possible that this difference occurs because of the information provided, or specific technology being proposed. There are few studies of women in the UK, but an international scoping review found women might need more training and technical support and may be less likely to have necessary technology (3.1.1).

4.3 Deprivation/employment/poverty

Deprivation, employment and poverty are known to be important social determinants of health. Without active intervention, AI training data and patient data may fail to consider these factors which might not be captured in healthcare data, but which a human might identify though nonverbal cues (2.2.2). Therefore, at best it is thought that AI might not address heath inequalities caused by these factors. At worse it could increase inequality, if the opportunity to provide other interventions is missed due to a narrow and medicalised focus, or because the individual cannot afford the Broadband and smart devices required to access the AI healthcare on offer (3.1.1).

4.4 Disability

Papers note that, as in healthcare more generally, disability can often be over medicalised by AI (3.2.1). Disability is a very broad group of people with very different backgrounds and needs. Overall, it is possible that AI could help provide personalised solutions which support people with different needs and make healthcare more inclusive and accessible for disabled people.

For AI to be accessible to as many people as possible, it is important that disabilities are considered, and accessibility is built in, and the technology can be tailored to work for the individual. For example, having options for both written and verbal interactions with the AI is better than having one or the other. Significant emphasis is placed on the importance of co-producing health outcomes with people with disabilities, and therefore having flexibility within the AI to enable tailoring to individual needs is particularly important (2.2.2).

There is perceived to be a significant risk of algorithmic bias for different disabilities – for example there is a potential risk of denial of healthcare if the outcomes are not set appropriately. There is also a risk of missing data or incorrect data relating to disability that could impact on how well an algorithm works (2.2.2). For example, for people with learning difficulties there might be a particular challenge due to perceived difficulties in securing informed consent (3.1.1).

4.5 Literacy/health literacy/education/English not as first language

As discussed elsewhere, if AI requires typed input, the literacy can be a barrier to use for some people (3.1.1). However, the increasing ability of AI to 'read out' text or have a conversation should reduce or remove this barrier, if the AI can understand the individual speaking.

There is evidence that not all voices are equal, and that AI can handle some accents and languages better than others (2.4.3). Equally, while it might understand the words being said, it may not understand the cultural nuances behind them. As such, generally the current literature points to using AI to augment and support translation, rather than necessarily to replace face to face translation services (2.4.1).

4.6 Gender/sexual orientation

The focus of discussion related to sexual orientation is the sensitivity of the personal data that is being processed to provide AI healthcare (3.1.1). As such, to avoid being a barrier to access, it might be valuable to have the option of not disclosing sexual orientation or otherwise minimising the data sharing necessary to use the AI. Again, the heterogeneity of this group should not be underestimated, and studies refer to the importance of balancing inclusivity and appropriate tailoring for specific groups. Particular gaps are noted for same gender–attracted women, trans and gender-diverse people, and people with intersex variations[122].

4.7 Pregnancy/marriage

There was no direct reference to any impact of pregnancy or marriage on the use of AI in healthcare, except passing mentions of cultural differences which may mean married women need to seek their husband's permission to use health technologies in some cultures (3.1.1).

There is data to show that Black women are significantly more likely to die within a year of pregnancy than White women (3.3), so it will be important for developers of AI to understand why inequalities such as this occur, and what role AI can play in minimising these differences in outcomes in the future.

4.8 Race and ethnicity

The main discussion about race and ethnicity relates to the risk of biased assumptions and bias in data sets relating to people from minority groups (2.2.2). Additionally, there can be historic reasons for higher mistrust in ethnic minority population groups, which might lead to individuals not disclosing their ethnicity, not agreeing for their data to be used, or not trusting AI in their healthcare (2.2.2). There are significant gaps in NHS data on ethnicity, and the ONS has shown that while NHS and census records match well for White British people, the NHS and census data for other groups (especially Black and mixed race) are much more inconsistent (2.2.2). Some groups, such as gypsy and travellers have lower levels of digital literacy, insufficient connectivity (old phone, limited internet access) and as such may encounter more problems if seeking to use AI in healthcare (3.1.1).

4.9 Religion/belief

There was only passing mention of religion and belief in the literature identified. This suggested that some people might follow religions or have beliefs that made them less likely to be willing to use AI. However, the search did not identify any empirical evidence or unpack which religions or beliefs might be related to different attitudes.

4.10 Asylum seekers/refugees

For refugees and asylum seekers, lack of language skills and difficulties accessing traditional mental health services for both physical and emotional reasons (shyness, embarrassment, fear, shame) can be a barrier to accessing care (3.1.2). Therefore, using AI can provide improved access to mental health support. However, there are concerns about data privacy and ensuring that the data will not be accessed by the police or immigration department.

4.11 Mental illness and substance use

The literature tends to focus on the use of AI to treat mental illness, rather than the impact of having a mental illness on the use of AI in healthcare more generally. The evidence for the use of AI in mental healthcare is mixed: some studies show that users perceive it to be useful, but others show limited empirical evidence that it leads to measurable improvements in outcomes (3.3).

One area in which AI might support access for people with mental illness is where anxiety prevents them from seeking help from a human. In some instances, the relative feeling of anonymity of when ‘speaking’ to a chatbot can be valued (3.1.2). Similarly, recent research demonstrated that AI might be better than a human at helping dispel conspiracy theories, through conversation[123]. However, perceived lack of empathy from AI remains a concern for some (2.2.2).

4.12 Geography - urban/rural/coastal

There is limited discussion of the impact of geography in a UK setting. The only relevant data identified related to access to high-speed broadband, where people living in rural areas were typically less likely to have a connection (3.1.1).

4.13 Homeless

A significant issue for homeless communities is digital access and trust. Specifically, because they may use public Wi-Fi to access digital services, their connection is unlikely to be secure or made in a private location. Therefore, they are less likely to be willing to access online services (3.1.1).

4.14 Criminal justice system

The searches found limited evidence about the impact of AI in healthcare on users of the criminal justice system. One scoping review looked at any digital health interventions including video calls. It found very limited evidence of the use of wearable devices although thought this could potentially be an area of opportunity for future study. It also found that technology was mostly being used to augment rather than replace existing services. It concluded that the use of technology in this way was found to be beneficial, although noted that the populations in studies were skewed (typically men) and that the sample sizes were not large, making it inappropriate to generalise[124].

5 Appendix

5.1 Notes on terminology

In this report several terms are used which may benefit from definitions.

5.1.1 Artificial Intelligence

While definitions of AI often refer to the ability of a machine to display human-like capabilities such as reasoning, learning, planning and creativity, there is currently no standard definition that has been widely adopted. Within the literature there are a wide range of examples of things that AI can do – from supporting diagnosis, to undertaking administrative tasks. Some technologies use generative AI, whereby the technology uses its learning to create something new. Others use deep learning to learn, extract and apply features from a dataset. In some cases, examples of more basic machine learning are also considered to be part of the AI field[125].

Specific studies may either define AI by giving a practical example of what it does that is relevant to the study (e.g. a tool that helps read x-ray images) or refer to AI generally, reflecting the range of different applications. For the purpose of this report we have adopted a broad definition which reflects the diversity of work underway. Where a specific example was used, this has been included for clarity.

5.2 Search approach

The searches for this report utilised PubMed, Embase and Google Scholar. The search terms outlined below were used to find initial relevant papers. Then a citation chaining technique was used which involved looking at their reference lists, Cited by, and Similar Articles in PubMed and Google Scholar. Each article found then went through that process.

This was supplemented with general Google searching looking for relevant reports (e.g. government, NHS or charity reports) and also looked any papers cited in those. The articles were collated then deduplicated.

The following terms were combined with Artificial Intelligence, AI with and without the mention of healthcare as an additional search term.

("addict*" OR "adolescen*" OR "Aged" OR "Aging" OR "Asian" OR "asylum seek*" OR "At-risk group*" OR "belief*" OR "bisexual*" OR "Black*" OR "Ethnicity" OR "carer*" OR "child*" OR "Chronic illness patients" OR "civil partnership*" OR "communit*" OR "criminal justice" OR "depriv*" OR "disabilit*" OR "disable*" OR "Disadvantaged communities" OR "discriminat*" OR "domestic violence" OR "Economically disadvantaged" OR "Elderly" OR "Ethnic minorit*" OR "exclude*" OR "exclusion*" OR "families" OR "family" OR "gay" OR "Gender" OR "Gyps*" OR "Health disparities" OR "HIV" OR "AIDS" OR "homeless*" OR "homosexual" OR "immigra*" OR "Incarcerated" OR "inequalit*" OR "Inequity" OR "Intimate partner" OR "Lesbian" OR "LGBT*" OR "Linguistic" OR "Language" OR "english" OR "literacy" OR "Low-income" OR "marginali*" OR "marriage*" OR "maternity" OR "mental health" OR "Migrant workers" OR "minorit*" OR "Non-binary" OR "older" OR "paediatric*" OR "pediatric*" OR "poor" OR "popula*" OR "poverty" OR "pregnan*" OR "protected charact*" OR "queer" OR "race" OR "racial" OR "refugee*" OR

"Religi*" OR "Roma" OR "rural" OR "Sexual Identit" OR "sexual orientation" OR "Sexual violence" OR "Social determinants of health" OR "Socially excluded" OR "substance abuse" OR "Substance use" OR "teenager*" OR "Trafficking victim*" OR "transgender*" OR "transsex*" OR "traveling" OR "Traveller*" OR "travelling" OR "undercounted" OR "underrepresent*" OR "underserved" OR "Undocumented" OR "Unemployed" OR "Victims of Violence" OR "vulnerable" OR "Women" OR "Working poor" OR "Young adults" OR "young people" OR "young person*" OR "youth*" OR "detention" OR "detained" OR "criminal record*" OR "parole*" OR "probation*" OR "ex-offender*" OR "offender*" OR "prison*" OR "inmate*" OR "custody" OR "faith*" OR "Christian*" OR "jew" OR "jewish" OR "jews" OR "judaism" OR "islam" OR "muslim*" OR "hindu*" OR "buddh*" OR "deaf" OR "hearing" OR "speech disorder*" OR "speech and language" OR "illiter*" OR "communication problem*")

These were combined with different topics e.g. Artificial intelligence

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