Family Medicine and Community Health

Artificial intelligence and health inequities in primary care: a systematic scoping review and framework

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ABSTRACT

Objective Artificial intelligence (AI) will have a significant impact on healthcare over the coming decade. At the same time, health inequity remains one of the biggest challenges. Primary care is both a driver and a mitigator of health inequities and with AI gaining traction in primary care, there is a need for a holistic understanding of how AI affect health inequities, through the act of providing care and through potential system effects. This paper presents a systematic scoping review of the ways AI implementation in primary care may impact health inequity.

Design Following a systematic scoping review approach, we searched for literature related to AI, health inequity, and implementation challenges of AI in primary care. In addition, articles from primary exploratory searches were added, and through reference screening.

The results were thematically summarised and used to produce both a narrative and conceptual model for the mechanisms by which social determinants of health and AI in primary care could interact to either improve or worsen health inequities.

Two public advisors were involved in the review process.

Eligibility criteria Peer-reviewed publications and grey literature in English and Scandinavian languages.

Information sources PubMed, SCOPUS and JSTOR.

Results A total of 1529 publications were identified, of which 86 met the inclusion criteria. The findings were summarised under six different domains, covering both positive and negative effects: (1) access, (2) trust, (3) dehumanisation, (4) agency for self-care, (5) algorithmic bias and (6) external effects. The five first domains cover aspects of the interface between the patient and the primary care system, while the last domain covers care system-wide and societal effects of AI in primary care. A graphical model has been produced to illustrate this. Community involvement throughout the whole process of designing and implementing of AI in primary care was a common suggestion to mitigate the potential negative effects of AI.

Conclusion AI has the potential to affect health inequities through a multitude of ways, both directly in the patient consultation and through transformative system effects. This review summarises these effects from a system tive and provides a base for future research into responsible implementation.

WHAT IS ALREADY KNOWN ON THIS TOPIC

⇒ There is a need for a comprehensive, holistic, conceptual framework of how the implementation of artificial intelligence (AI) can affect health inequity in primary care.

WHAT THIS STUDY ADDS

⇒ AI has the potential to affect health inequities through a multitude of ways, both directly in the patient consultation and through transformative system effects.

HOW THIS STUDY MIGHT AFFECT RESEARCH, PRACTICE OR POLICY

⇒ This review summarises these effects from a system-wide perspective and provides a base for future research into responsible implementation.

INTRODUCTION

Artificial intelligence (AI) can be described as a computer system performing tasks typically requiring human intelligence. Everyday examples include predicting preferences in social media feeds and recognising faces in photos.[1] It is a rapidly expanding field, and AI-augmented interventions are high on the agenda across healthcare, where current application include interpreting X-rays and ECGs. Current implementation of AI-augmented systems within healthcare is currently low but advocated widely as the future and in strategic solutions. Thus, AI systems of varying kinds are expected to be widely implemented across the healthcare system over the next decade, and primary care is no exception.[2]

At the same time, health inequities (HI) are being increasingly discussed, not least in the context of the ongoing COVID-19 pandemic.[3] Through potentially freeing up resources and enabling more personalised care, AI is described as an enabler for more equitable health and healthcare.[2] However, AI interacts with socioeconomic, gender and ethnic HI on many different levels and could

both increase or decrease inequities, depending on application and implementation.[4 5]

Primary care holds a unique role in tackling HI. Primary care can both be a source and a magnifier of inequities, as well as a platform for mitigation.[6] For the purpose of this review, primary care is defined as primary care services provided to individual patients, not including wider public health policy.[7] Primary care can be inaccessible to certain groups and thus worsen HI, but at the same time is usually the first contact point for socioeconomically disadvantaged populations with either health or social needs. While the theoretical access to primary care and clinical management has been shown to be relatively equal across groups, outcomes still differ, with more affluent patients of majority ethnicity enjoying better health.[8] This is a consequence of external factors causing poorer baseline health status and through differences in effectiveness of the care given, due to adherence to treatment and advice, economic barriers and so on; the social determinants health (SDH).[9] Consequently, as care need increases by deprivation, more primary care resource is needed to provide adequate care in disadvantaged areas and communities.[10] To summarise, the role of primary care in reducing HI is not just through addressing inequities within primary care, but to leverage its unique position in society to mitigate underlying differences in health outcomes.[10] This is reflected in the way AI could affect inequities both in and through primary care.

However, as this review shows, 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.

Applying a systematic scoping review approach, this article takes a holistic approach to create a comprehensive model for how AI can affect HI, in and through primary care. As such, we intend it to serve as guidance to develop future research, regulations and policies surrounding AI, primary care and HI. This review assumes a predominantly publicly funded, general access primary care system, such as the British National Health System (hereafter NHS), however, certain mechanisms described may be applicable in other primary care systems as well.

As research into the practical implications of AI on healthcare provision is still relatively limited, our objectives were intentionally broad to capture as much of the field as possible. Thus, a scoping review was chosen as the appropriate methodology to meet our study aims. This allowed for an iterative strategy, with the objectives adjusted as the field was explored.[11]

Specifically, our review sought to answer the following questions (hereafter discussed as objectives):

1. What research currently exists on the effect of AI on primary care equity?
   a. How does the evidence-based match a provisional conceptual framework that we developed from our initial exploratory searches?
   b. Through which methodologies have the topic of AI and primary care equity been studied?
2. How is the patient–doctor relationship assumed to be affected by an increased usage of AI in primary care, and what are the implications for primary care equity?
3. How can the implementation of AI in primary care affect wider population inequity?

METHODS

This review was informed by the scoping review framework originally described by Arksey and O'Malley,[12] and subsequent developments.[11 13] As the searches in this review were conducted following a systematic approach, we chose to describe the methodology as a systematic scoping review, in line with previous guidance.[13] The report was structured and written in accordance with the scoping-review reporting standards as set out by PRISMA (Preferred Reporting Items for Systematic reviews and Meta-Analyses).[14]

EndNote[15] was used to manage the selection process, while Microsoft Excel[16] was used for charting and extraction.

Public involvement

Two reimbursed public advisors (members of the public recruited through the National Institute for Health and Care Research Applied Research Collaboration North West Coast; NIHR ARCNWC) were involved in this review, both belonging to traditionally marginalised populations (one of British Asian ethnicity and one registered disabled and member of the LGBT (Lesbian, Gay, Bisexual, and Transgender) community). They participated in proofreading and approving of the protocol, assisted in selecting and extracting publications, and commented on the analysis and the findings. Public advisor involvement is intended to increase relevance and clarity of the review, and offering a non-academic perspective and interpretation. Given the review's focus on equity and inclusion, this was seen as particularly relevant.

Public involvement is reported throughout this text, following the GRIPP2 framework,[17] and as a checklist (online supplemental annex 4).

A provisional conceptual framework

Having an initial conceptual framework of the topic is a useful tool to guide the review process.[11 12] From the initial exploratory searches, which consisted of targeted internet searches and reading based on the experience of the authors, we constructed a provisional framework for how AI could affect healthcare equity in a primary care setting (online supplemental annex 1). We drew on work by the WHO Commission on SDH,[9] Marmot *et al*,[18] Dahlgren and Whitehead,[19] and Veinot *et al*[4] on how SDH may affect equity in and through primary care, and applied a layer of how AI may affect the various steps of the care process.

Demographic characteristics of patients (here on pragmatic grounds limited to socioeconomic status, gender and ethnicity) both give rise to baseline HI and affect the way the patient interacts with the healthcare system,

through SDH.[9] For the purpose of this review, we considered these effects through a model developed by Veinot *et al*,[4] where HI in care provision arise from either access, uptake, adherence or effectiveness.

Effects of AI were, using this framework, divided into intrinsic effects from the actual AI (such as biased outputs) and extrinsic covering potential effects on the wider healthcare provision, outside of the direct implications of the algorithm (such as making access to care easier or harder for disadvantaged groups).

n addition, in our provisional framework, we acknowledged that the implementation of AI in care provision is likely to have complex, system-wide effects which in turn will affect the care systems' ability to mitigate HI.

Eligibility and inclusion

Initial searches indicated a distinct lack of robust primary empirical research (with a few notable exceptions) as well as little research conducted using secondary data, for example, data that were initially collected for direct care purposes or reviews. Thus, we decided to widen the scope and included descriptive sources including discussion articles and policy documents, to seek empirical evidence and construct our model. For the primary objective (current state of research) and tertiary objective (impact of implementation), searches included all forms of healthcare to maximise yield, with selection of articles relevant for primary care taking place in the next step. For example, Obermeyer *et al*'s article on resource allocation for multimorbidity care[20] does not cover primary care, but was included as the equity-related concepts are transferable to the primary care context.

AI was for the purpose of this review limited to clinical applications, following Shaw *et al*'s[21] typology of AI in healthcare. This includes AI-driven decision support systems and automated healthcare (such as automation of insulin or autonomous advice given to patients without human involvement), but not operational such as planning patient flows or staffing needs. This includes both on-site and telehealth applications of AI, with the defining feature being AI-driven decision-making affecting patient care directly. Primary care was defined as primary care services provided to individual patients, not including wider public health policy, as per Muldoon *et al*.[7] HI was defined widely as socioeconomic, gender or ethnic inequities in health outcomes, as outlined in the provisional conceptual framework and reflected in the search terms (online supplemental annex 2).

Searches were limited to the last 10 years (26 October 2011 to 26 October 2021), because AI was not being delivered in practice in primary care before that date.

We only considered publications in English and Scandinavian languages, due to the main author being bilingual in Swedish and English. Other languages were excluded due to resource limitations.

See table 1 for inclusion criteria.

Table 1 Inclusion criteria

	Inclusion criteria (any of the below)
1.	They discuss artificial intelligence interventions in healthcare with an explicit focus on equity, either in or applicable to primary care (objective 1), artificial intelligence in primary care provision (objective 2) or practical implementation of AI in a system and the subsequent role of the infrastructures, organisational processes and personnel involved (objective 3).
2.	They are published by either a peer-reviewed journal or by a major governmental or non-governmental organisation.
3.	The full text is available in English or Scandinavian languages.

AI, artificial intelligence.

Information sources

Electronic databases were searched using a set of keywords with varying syntax depending on database, MeSH (medical subject headings) terms when possible. Three major databases for medical and implementation research were searched; PubMed, Scopus and JSTOR. Grey literature in the form of reports and white papers by major governmental and non-governmental organisations was included. The complete search terms are listed in online supplemental annex 2.

To maximise the number of publications retrieved, we followed the systematic searches with secondary reference screening from the references of the included articles. The publications identified through this method were scanned for inclusion in the same way as the articles initially identified. At the end, articles found through initial exploratory searches were included, and their references scanned for relevant literature.

Selection process

We conducted screening and selection in two stages: first, abstracts were screened and reasons for exclusion recorded. The remaining articles were read in their entirety and reasons for those then excluded were recorded.

Initial screening of the first 100 abstracts were conducted jointly with two public advisors, building a joint understanding of the selection criteria. These discussions clarified and simplified our criteria. The remaining titles and abstracts were primarily screened by the main author (Ad'E). Thirty per cent of the abstracts were double screened by the two public advisors and a coauthor (EJ) (10% each). The same process was repeated for full-text screening. Disagreements were decided through consensus, leaning towards inclusion.

Data extraction

We based the data charting form on this provisional framework and review objectives, and included six topics (table 2) (complete extraction table in online supplemental annex 3). Themes were based on the provisional framework (online supplemental annex 1) with a low threshold for introducing new themes. The main author was responsible for the data extraction at large and

Table 2 Data charting

Data charting	
1.	Year of publication, country of origin and type of paper; discussion article, policy paper/white paper, empirical study, review.
2.	Does it cover primary care, other specialties, healthcare in general or another discipline?
3.	Summary of article and main points in relation to the objectives.
4.	Relation to the provisional framework; does it relate to one or more of the provisional themes, does it challenge the model, or does include a theme not in the model?
5.	Does the article describe how the implementation of AI can affect the patient–doctor relationship, and how this could have implications for healthcare equity?
6.	Does the article describe the role of infrastructures, organisational processes and personal involved in implementing an AI system, and how the implementation could affect healthcare equity?

AI, artificial intelligence.

charted all included sources. In addition, the two public advisors together extracted ten percent of the total yield, after which a meeting was held with the main author to discuss the process and the results to improve the consistency of the extraction process.

Absence of critical appraisal

Given the wide scope as well as the lack of a large body of original research on AI and HI, most results from the searches were non-empirical papers. Our objectives did not include an appraisal of the quality of evidence, as appropriate for the lack of original research, and we did not give preference to specific types of sources, which was reflected in the narrative interpretation of the results.

Synthesis of results

For the primary objective, we summarised the charted data in relation using thematic analysis, described among others by Levac *et al*.[11] Themes were based on the provisional conceptual framework (online supplemental annex 1), which combined established theory on SDH[9 19] (ie, a positivist sociological approach) and inequity in health technology,[4] the latter building on the health-system-inequity model by Tanahashi.[22] Following the thematic analysis model,[11] the main author reviewed the charted data and analysed it against the themes of the provisional framework, keeping a low threshold for introducing new themes or modifying the framework. The result of the synthesis was discussed among all authors for clarity. The two public advisors were invited to comment on a draft of the review and contributed with clarifications. The results are presented as a graphical model of a conceptual framework for how AI affects health equity in primary care, as well as a narrative description of the state of the research in the field and scope for future work. For the secondary (patient–doctor relationship) and tertiary (impact of implementation) objectives, data were summarised thematically for respective objective, to inform how of AI in primary care can be implemented as force for good from a HI perspective.

RESULTS

Selection of publications

We found 1504 publications in the initial searches. After exclusions, 164 publications were read in full, of which 67 fulfilled the inclusion criteria, 19 further secondary references were identified from the reference lists of these 62 articles, of which 13 were included. Finally, we included six key publications found during the initial exploratory searches for completeness. See figure 1 for PRISMA[14] chart. Discussions with public advisors contributed to two additional inclusions.

Characteristics of publications

The most common type of publication (n=45) were discussion articles, followed by original research (n=18), reviews (n=17) and reports/policy documents (n=6). Of the original research sources, eleven reported on quantitative studies, while seven used a qualitative methodology. Of the 17 reviews, 15 were narrative reviews and 2 were quantitative systematic reviews. The USA was the most common country of origin (n=40), followed by the UK (n=23) and Canada (n=9). Publications were all recent; the publication years ranged from 2017 to 2021 (mean=2019.9, median=2020). As previously noted, searchers were not limited to sources discussing primary care, but included sources discussing other kinds of healthcare covering concepts applicable to equity in primary care. Approximately half of the publications discussed healthcare on a general level (n=48), 20 discussed primary care (which was explicitly searched for) and 6 discussed psychiatry, followed by smaller topics with fewer papers. Five articles discussed AI on a general society level (table 3).

Summary of findings

The themes were not necessarily discrete, and one specific concept may fit under several themes. For example, a lack of diverse representation in developing an AI system may lead to unintended inequities through: (1) a lack of an equity-lens during development, enabling an unfair problem formulation,[20] and (2) lead to unfair system effects external to the algorithm.[4]

The findings are summarised below, and in a graphical conceptual model of how AI could affect socioeconomic, ethical and gender-based inequities in primary care (figure 2).

Objective 1: in what ways may AI effect HI in a primary care setting?

Algorithmic bias

Algorithmic bias was discussed in 59 publications. Biased outcomes stemming from the AI itself (in contrast to the AI system's interaction with external factors) can broadly be categorised within two categories; unrepresentative

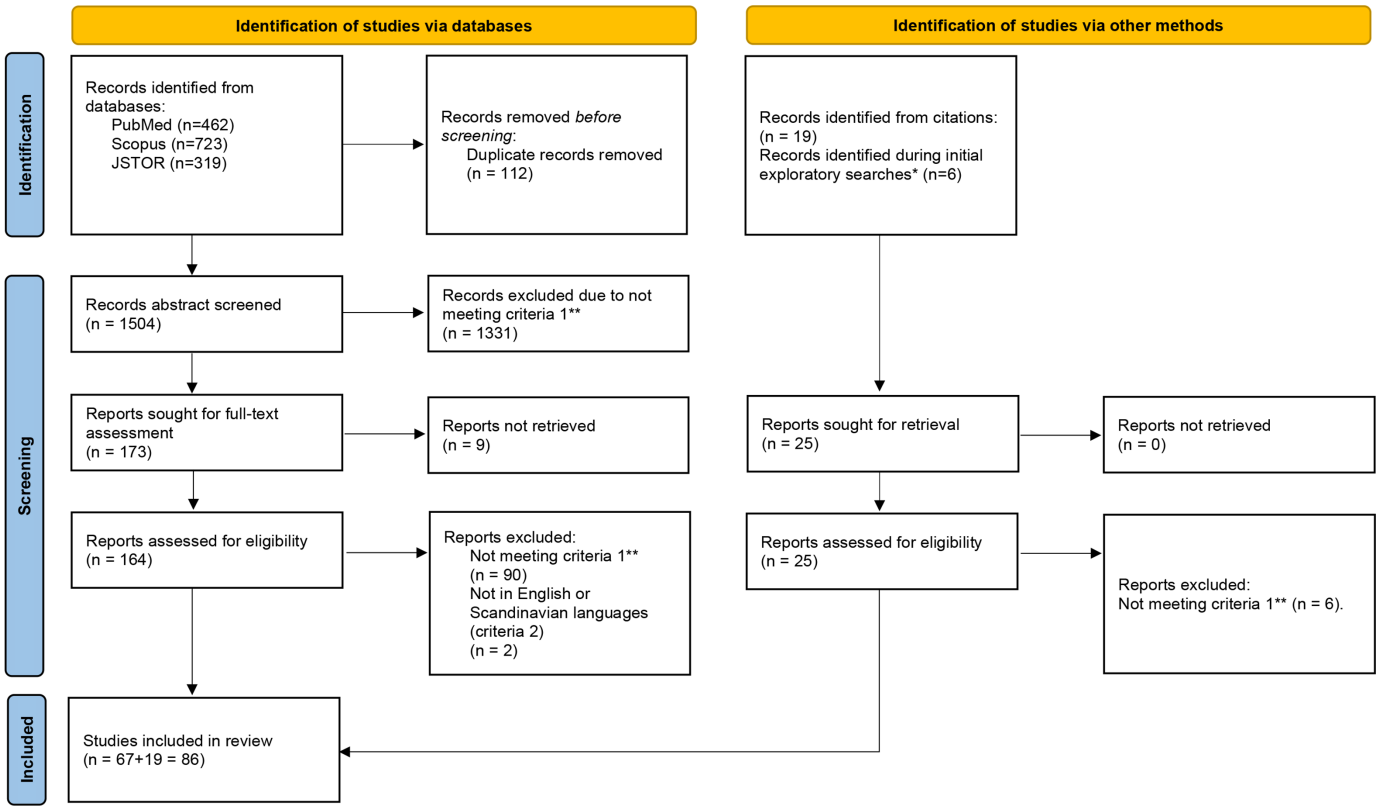

Figure 1 PRISMA chart of search and selection process. *If not included in database searches. **Criteria 1: Discussing artificial intelligence interventions in healthcare with an explicit focus on equity, either in or applicable to primary care (objective 1), AI in primary care provision (objective 2) or practical implementation of AI in a system and the subsequent role of the infrastructures, organisational processes and personnel involved (objective 3). All records retrieved met criteria 3: Published by either a peer-reviewed journal or by a major governmental or non-governmental organisation. AI, artificial intelligence; PRISMA, preferred reporting items for systematic reviews and meta-analyses.

datasets and underlying biases reflected in the datasets. Under-representation of various populations in the datasets used to train AI algorithms may result in less accurate outcomes for these groups, for example, ethnic minorities. The main concerns relate to skewed outcomes when an AI is better fitted for one group than for another. Among others, Chen *et al* showed this in relation to intensive-care-mortality prediction, which was shown to be more accurate for Caucasian men compared with women and patients of minority ethnicities.[23]

A fundamental concept was reiterated across the literature identified: SDH are present in society, and when a model is based on real-life data, it may reflect and potentially reinforce the effect of SDH (ie, HI). Examples include Obermeyer *et al* who found that a widely used AI system for selecting multimorbid health insurance patients for extra resources (in order to prevent future deterioration and costly care) requires African-American patients to be significantly more ill to access resources.[20] The issue was not in the quality of the dataset, but that the system developers used historical healthcare costs as a proxy for current morbidity. The authors showed that African American patients use less care resources for the same morbidity, and the AI thus perceived them to be less ill compared with their Caucasian counterparts. Samorani *et al*[24] described how ethnic minority patients are given worse time slots by automatic primary care booking systems due to higher rates on non-attendance, leading to even less attendance. Their study thus serves as an example of how biases could reinforce and perpetuate inequities already present in society.

Increased access and the digital divide

Accessibility aspects were discussed in 21 publications. AI may lead to increased access as an enabler for more equal healthcare provision. However, increased access also brings a risk for the healthcare system being overwhelmed by the 'worried well'.[5] Fiske *et al*[25] discussed the risk of creating a two-tier system, where AI-augmented psychiatry disenables the option to provide 'human services' in rural and underserved areas.

Conversely, the 'digital divide' was frequently discussed, not just regarding digital availability but also functional access. This was not only an issue of possessing the technology and infrastructure needed to interact with a digitalised care system, but also having the skills to fully make use of it, as well access to a private room.[26 27]

Related to accessibility, Clark *et al*[28] highlighted the opportunity of using AI to predict population-wide morbidity and identify the social determinants driving HI from a primary care and psychiatry perspective. Thus, AI

Table 3 Characteristics of publications

Category	No (%)
Type of publication	
Discussion (including book chapter)	45 (56)
Review, narrative	15 (19)
Review, systematic quantitative	2 (2)
Original research, quantitative	11 (13)
Original research, qualitative	7 (9)
Report or whitepaper	6 (7)
Setting for study or discussion	
General healthcare	48 (59)
Primary care	20 (25)
Psychiatry	6 (7)
Ophthalmology	3 (4)
Diabetes	2 (2)
Radiology	1 (1)
Oncology	1 (1)
Non-specific	5 (6)
Country of origin	
USA	40 (49)
UK	23 (28)
Canada	9 (11)
Switzerland	3 (4)
Australia	1 (1)
Denmark	1 (1)
France	1 (1)
Italy	1 (1)
Japan	1 (1)
Netherlands	1 (1)
Norway	1 (1)
Portugal	1 (1)
South Africa	1 (1)
Year published	
Mean and SD	2019.9 (1.05)
Range	2017–2021
Total	81

could, in this application, help to address these factors and subsequently improve equity.

Trust of patients

Trust aspects were discussed in ten of the publications. A recurring theme was that historically discriminated groups may be less inclined to trust and thus take advantage of AI. Veinot *et al* argued that ethnic minorities are more sceptical to digital health interventions than the majority population,[4] a conclusion shared with Marcus *et al*, who in their review, stated that privacy and security issues are major causes for distrust in AI among minority ethnicities.[29] Involving the effected communities in the development and implementation of the AI tools were again held as a key to mitigate this, among others by Howard and Borenstein.[30]

In contrast, Bigman *et al* found that the tendency to prefer the AI over a human doctor increased with the patient's perceived underlying societal inequity; African-Americans became more likely to prefer the AI compared with Caucasians when there was a higher perceived 'background' of inequity.[31]

Dehumanisation and biomedicalisation

Dehumanisation was discussed in 19 publications. As Coiera[32] states, more biomedicalised healthcare system may have adverse impacts on patients with complex needs, who disproportionally are from socioeconomically disadvantaged groups and of a minority ethnicity. The only included empirical study on impacted populations was by Miller *et al*,[33] who surveyed users of a primary-care-triage AI-driven chatbot. Older patients with co-morbidities were less likely to both use and to appreciate the interventions, compared with young and healthy participants. Given that the prevalence of psychosocial morbidity is known to follow a socioeconomic gradient, it can be extrapolated that such developments would increase HI.[8]

However, Fiske *et al*[25] hypothesise that such developments may have a beneficial effect on certain inequity issues relating to acceptability and perceived stigma, for example, concerning sexual health and psychiatric illness.

Agency for self-care

Four publications discussed patient agency and HI. HI may arise from an increased focus on patient-managed healthcare because of increased AI-utilisation. Kerr and Klonoff discussed the issue in relation to diabetes management, where there is an established difference in attitudes and ability to self-care in-between socioeconomic groups at the present.[34] Such socioeconomic gaps may widen unless AI interventions are properly tailored for the populations that they are deployed in. This closely aligned with the established concept of downstream interventions being inherently inequitable.[4]

Objective 2: how is the patient–doctor relationship assumed to be affected by an increased usage of AI in primary care, and what are the implications for healthcare equity?

The topic was discussed in 13 sources. As aforementioned, AI may lead to a shifting emphasis from social circumstances (including wider social determinants of health) to measurable, objective observations. Such developments may worsen inequities, in particular with regard to morbidity related to psychosocial factors. Romero-Brufau *et al*[35] conducted qualitative interviews with primary care staff before and after the implementation of an AI-driven diabetes support tool; the AI tool was perceived to give biomedically sound recommendations but overlooked psychosocial factors that may have led to suboptimal diabetes control in some patients and was seen as not providing equitable care by the staff.

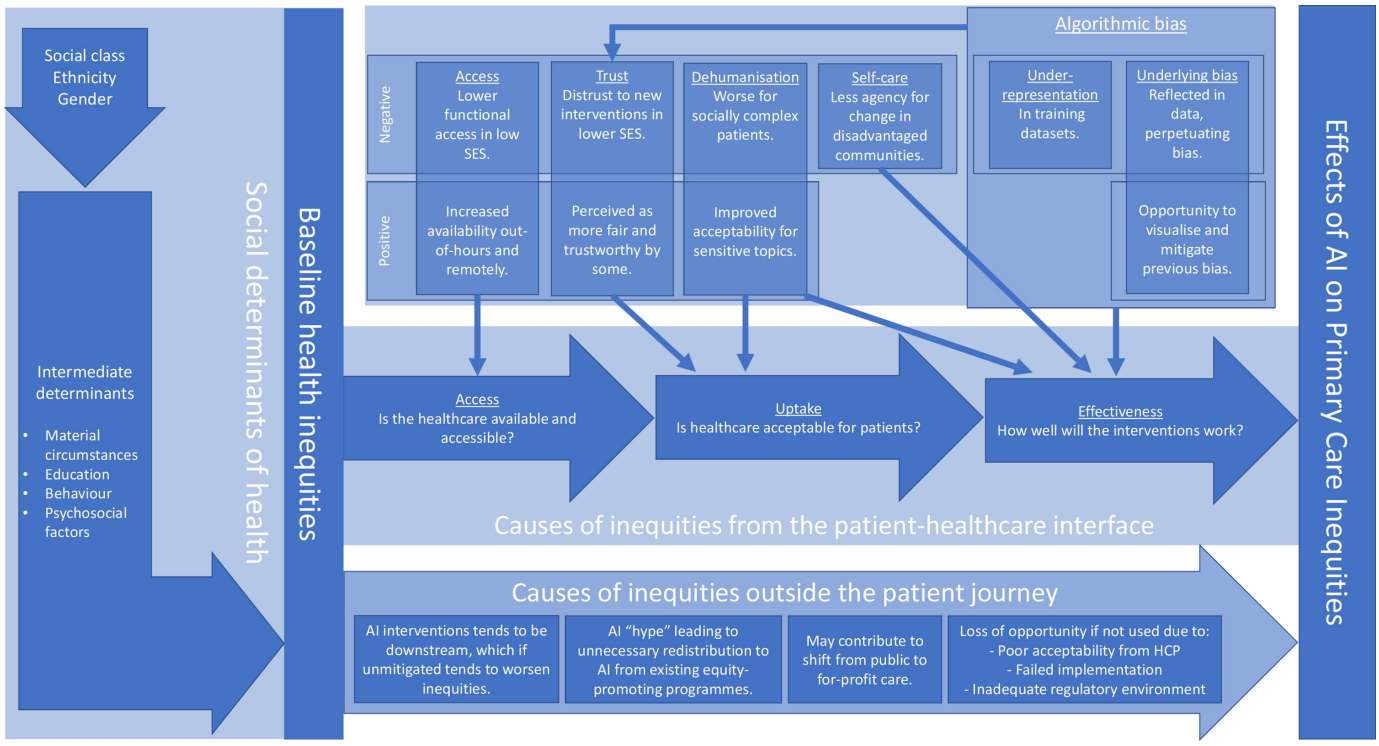

Figure 2 A conceptual framework for how AI could affect inequities in primary care. AI, artificial intelligence.

Surveying general practitioners (GPs) directly, Blease *et al*[36] found that 94% of GPs believed that AI would be unable to replace GPs in roles requiring empathic ability, over any time scale, a perception shared with informaticians interviewed by the same team.[37] Along the same lines, Holford[38] and Powell[39] claimed that an integral part of the role of the doctor inevitably gets lost if the practice is translated into an algorithm. Using an anthropological perspective, Holford discussed this as the loss of deep knowledge, experience and intuition in relation to AI and technological progress. As tasks and jobs are broken up into simple standardised lists, implicit knowledge and intuition inevitably are lost, and it is currently impossible to replicate using AI. This would subsequently affect those in most need of compassion and holistic care.

Objective 3: how can the implementation of AI affect inequity?

Implementation aspects were discussed in 47 publications.

Participatory approaches and community involvement

Lack of diverse participation and community involvement was a risk factor for unequitable AI-interventions in healthcare, both in development and implementation of AI systems in the existing primary care system.[20 40] Involvement of the target community throughout the whole implementation chain, from idea and problem formulation via data collection, datasets and regulatory environment all the way through implementation and end-users was key for equitable AI in general healthcare and primary care.

Alami *et al*[41] and Clark *et al*[42] argued that there is an urgent need to 'mainstream' a fundamental understanding of AI and its potential effects on healthcare and health equity among both clinicians and policy makers. This serves both to build trust and enable an understanding of when and how a specific AI intervention is suitable and what can be done to optimise the equity effects of its implementation. Holzmeyer[43] emphasises a comprehensive equity analysis as the starting point of all system interventions in healthcare: what is the root cause behind what we are trying to address; what are the relevant SDH; what are the historical contexts; and to what extent do stakeholders agree on these issues?

Acceptance from care providers, loss of opportunity and equity

Failed implementation may affect inequities both through loss of potentially equity-improving AI systems, and through pushing new technology to uncontrolled consumer products such as smartphone apps, leaving the traditional health system unable to manage increased health anxiety and care-seeking.[2 44 45] Williams *et al*[45] created a framework specifically focused on ensuring sustainable AI-implementation, emphasising the need to consider the system-wide external effects from new interventions.

Primary care clinicians may be too busy and lack organisational resources to effectively adopt new technologies, risking poor uptake and leaving the field open to the commercial sector, more likely to cater to the 'young and well'.[40 45 46] Clinicians faced with an AI system perceived to not take SDH and personal circumstances into consideration may lose trust in AI technology at large, and object to further implementation, as discussed by Romero-Brufau *et al*.[35] Alternatively, resistance will occur if they perceive that an AI intervention is pushed on them 'for the sake of it' rather than to solve a specified problem, as noted by Shaw *et al*.[21]

Ferryman *et al*[47] suggested that an overemphasis on agility and rapid change in the regulatory environment causes a risk of equity-adverse products being implemented in the healthcare system. The potential conflict of interest between a fast-paced regulatory environment and a healthcare system inherently focused on safety and thorough evaluation was also highlighted in a recent NHSX (a digital innovation arm of NHS) report[2] and by the WHO,[48] among others. As discussed in the previous section, this may result in a loss of opportunity to improve healthcare equity, and again 'handing over the ball' to the commercial sector.

Overconfidence in AI, fuelled by the perception of AI as a novel, exciting and superior technology delivered by commercial companies developing the systems, as well as a public 'mythology' around its superiority (as expressed by Keyes *et al*[49]) may displace other more effective programmes for addressing HI, such as addressing the SDH directly, and working with community groups.[48]

In a wider context, upstream interventions such as public health measures and direct action to SDH have been proven to be more effective in reducing inequities than downstream interventions, such as changes in care provision or new therapeutic options. As such, like any intervention without explicit equity focus, AI interventions in primary care may be intrinsically unequitable.[4]

DISCUSSION

Building on the themes identified above, the graphical conceptual model (figure 2) emphasises AI's potential HI effects both inside and outside of the patient journey. That is, outside the patient journey meaning mechanisms not directly related to how patients interact with the primary care system. This highlights the importance of a system-wide perspective and of the concept of HI to be mainstreamed throughout the development and implementation process.

While there was limited research connecting AI with the dehumanisation of primary care (a trend towards replacing clinicians with AI-augmented technology) and HI, a few assumptions can be made, in particular:

The role of primary care as a mitigator and improver of HI is dependent on primary care clinicians being able to contextualise the care provided, work 'outside the box' and see to the social factors influencing patients' health. This may involve recognising that a patient may not be able to stop smoking because she is currently worried about becoming homeless, or it may be necessary for a GP to deliver health motivating messages adapted to the individual's unique circumstances.

The prevalence of illnesses with a psychosocial component is heavily associated with low socioeconomic status,[50] and to effectively support such patients requires understanding of, and the ability to deal with, the underlying causes. A purely biochemical approach to medicine is insufficient, particularly within more disadvantaged communities.

Conclusively, there is a risk that such developments, if done without equity in mind, would unduly affect the healthcare of socioeconomically disadvantaged communities, and thereby worsen HI.

The way AI is implemented is integral to how well it interacts with the current systems and societal context, and by extension how it affects HI. Multiple publications discussed the risk of AI-augmented interventions being directed towards the young, healthy and well-off. This is because the disruptive traits of AI enables commercial providers to expand beyond comparatively costly and complicated human clinicians, for example, by smartphone apps. A recent case from Babylon Health is a GP at Hand system, where an AI-driven smartphone app enables users to be triaged, diagnosed or forwarded to a clinician directly from their phone. Initially, GP at Hand explicitly blocked patients with complex health needs from registering with them. Babylon Health was consequently accused of 'cherry picking' patients for whom their AI could care for sufficiently, leaving the complex patients to the traditional primary care centres, who in turn, would see an increase workload while being drained for resources.[27] While this clearly was a regulatory loophole which subsequently was addressed, it highlights the risk of AI being used to disrupt and commercialise the primary care system, and the inherent tendency to go after the 'easy', tech-savvy patients first.

Social participation in developing and implementing AI interventions was prominent in the publications, as a way of promoting locally appropriate adaptation. While specific methods were not discussed in detail in the reviewed publications, a recent 'citizen's jury' on AI and explainability provides an example of how it could be done.[51] A similar approach could also be used to ensure regulatory frameworks for AI in healthcare aligns with the affected populations.

The need to 'mainstream' health equity throughout the whole implementation chain was a clear finding. Ensuring a system-wide basic understanding of SDH, HI and the role of primary care in addressing HI could help identify and avoid adverse effects.

Finally, there is clearly a need to look outside of the isolated clinical context in assessing the impact of AI in primary care on HI. Most of society's HI occurs outside of the primary care system as a consequence of SDH, and that is also where interventions to address inequities are bound to be most effective. Downstream interventions, such as clinical AI, by default tend to worsen inequities because more advantaged groups usually benefit the most. As Holzmeyer[43] put it, the most important goal of AI in terms of HI is thus to do no bad, which by extension means it has to be explicitly and actively equity-promoting. More research is needed on the most effective ways of how to both design and assess new interventions from such holistic perspectives. We suggest that a useful output of such research could be guidance in the form of considered steps or a framework that includes equity considerations to prevent fundamental mistakes being made that invertedly generate wider inequalities.

As outlined above, two public advisors made a significant contribution to the review, both through discussions on inclusion criteria and publication selection and through contributing with an outside perspective.

The review set out to cover HI related to ethnicity, gender and socioeconomic status. Most included publications discuss HI generally, focusing on concepts applicable to various forms of HI. We recognise that while the fundamental mechanisms in which inequity occur are shared across disadvantaged demographic groups, there is a further need to specifically study discrimination by specific characteristics, also including wider ranges of marginalised populations.

Finally, available resources limited us in doing further secondary and tertiary reference screening, as well as more detailed searches with lower-level terminology, and so there was a small risk that articles were not included that would have been eligible. Nine articles initially identified could not be retrieved, introducing a risk of selection bias, although proportionally small. Resource limitations also limited the searches to the English and Scandinavian languages. Nonetheless, we are confident that this review provides a representative and largely comprehensive summary of the current state of research.

CONCLUSION

Using a systematic scoping review methodology, we have mapped the current research on AI and HI in the context of primary care, and synthesised the findings into a conceptual framework; a theory of change. At the centre of this framework is the graphical depiction (figure 2), which combines established research on SDH and HI with themes identified in the reviewed literature and provides a holistic overview of the mechanisms at play.

We highlight the complexity of assessing such a diverse concept as AI. While AI in primary care covers a wide array of current and potential applications, there are common traits inherent to AI as a technology. AI can be considered a core component of an ongoing paradigm shift in healthcare provision, perhaps most comparable to the rapid biomedical and pharmacological progress of the beginning and middle of the last century.

From the findings, we note that academics as well as the regulatory establishment are still finding their way around AI in healthcare. We identified a relative wealth of publications covering algorithmic bias, but in terms of original research, very few publications discussed the wider impact of AI on patient care and the primary care system at large. Given the intersectoral and dynamic nature of HI and SDH, a wider perspective is needed to properly assess the potential effect of widespread AI implementation in primary care. No interventions can be implemented in isolation and the role of the surrounding society, organisational infrastructure and regulatory frameworks cannot be overstated. All aspects need to be considered to implement equitable AI in an environment conductive for improving equity.

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Contributors Ad'E designed the review, conducted the searches, screened all articles, conducted the analysis, drafted the manuscript and acts as the guarantor for the overall content. MG, SR and CK assisted in designing the review and reviewing the manuscript. EJ coscreened 10% of the abstracts and 10% of the full-length articles. ID and AT provided feedback on the design as public advisors, and each coscreened 10 % of the abstracts and 10% of the full-length articles. They also provided feedback on the analysis and the manuscript. LF assisted in designing the review as the primary PhD-supervisor of the first author Ad'E, and assisted in reviewing the manuscript.

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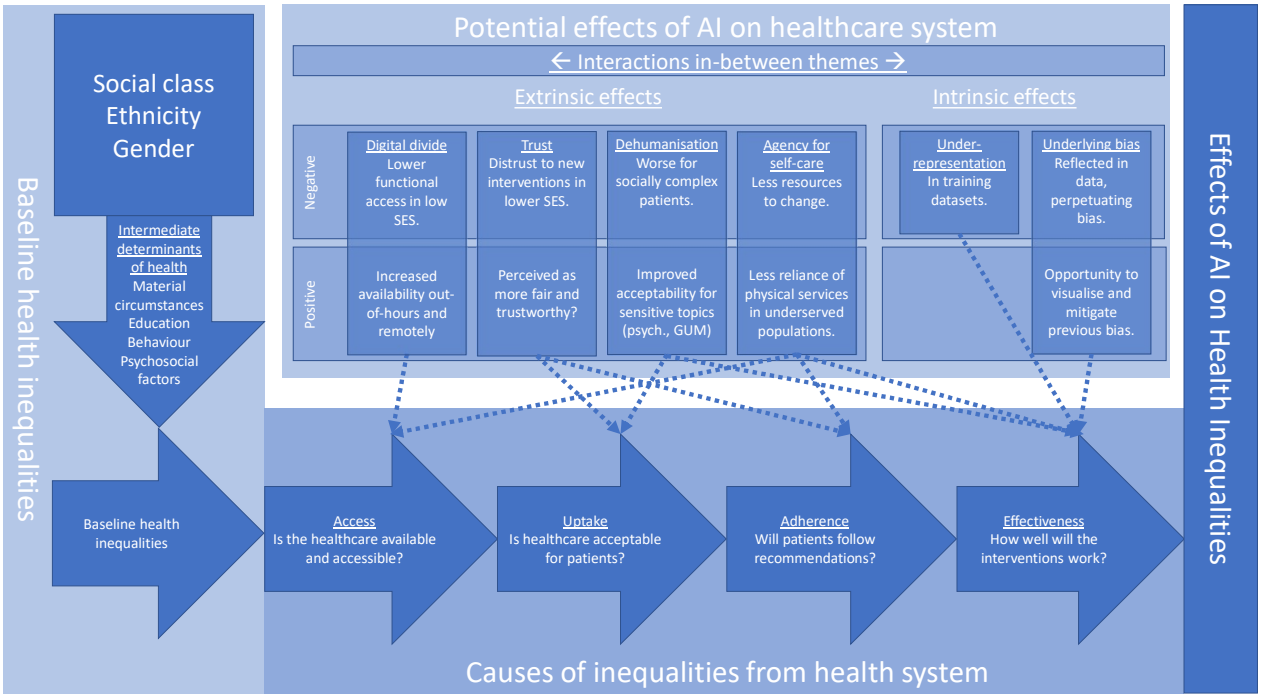
Annex 1: A priori conceptual framework of AI and HI in primary care



A priory conceptual framework for how AI may affect health inequities in and through primary care.

Annex 2: Search terms

Database → **Topic covered**	**Pubmed/Medline** (MeSH where possible) All 10yr+Eng	**Scopus** (And other databases with no MeSH) All 2011 + Eng	**JSTOR** Journals, 2011, Eng
Ai and health equity.	("artificial intelligence"[MeSH Terms]) AND (("Health Services Accessibility"[MeSH Terms]) OR ("human rights"[MeSH Terms])) 588 (10 yr, English) Note: Equity falls under Human Rights in MeSH.	TITLE-ABS-KEY ("artificial intelligence" AND "health" AND ("human rights" OR inequality OR equality OR equity OR inequity OR accessib*)) AND (LIMIT-TO (PUBYEAR , 2021) OR LIMIT-TO (PUBYEAR , 2020) OR LIMIT-TO (PUBYEAR , 2019) OR LIMIT-TO (PUBYEAR , 2018) OR LIMIT-TO (PUBYEAR , 2017) OR LIMIT-TO (PUBYEAR , 2016) OR LIMIT-TO (PUBYEAR , 2015) OR LIMIT-TO (PUBYEAR , 2014) OR LIMIT-TO (PUBYEAR , 2013) OR LIMIT-TO (PUBYEAR , 2012) OR LIMIT-TO (PUBYEAR , 2011)) AND (LIMIT-TO (LANGUAGE , "English"))	((((("artificial intelligence") AND ("healthcare" OR "health care")) AND (equality OR equity OR inequality OR inequity))))) AND la:(eng OR en)
AI's impact on primary care provision.	("artificial intelligence"[MeSH Terms]) AND (("general practice"[MeSH Terms]) OR ("primary care"[All Fields]))	"artificial intelligence" AND ("general practice" OR "primary care")	("artificial intelligence") AND ("general practice" OR "primary care")
Practical implementation of AI in a system and the subsequent role of the infrastructures, organisational processes and personal involved, *and how implementation could affect inequality.*	("artificial intelligence"[MeSH Terms]) AND (("general practice"[MeSH Terms]) OR ("primary care"[All Fields])) AND (("implementation"[All Fields]) OR "social practice" OR "technology-in-practice")	((("artificial intelligence" ("general practice" OR "primary care") "implementation")) OR ("artificial intelligence" ("social practice" OR "technology-in-practice")))	("artificial intelligence" OR "machine learning") ("social practice" OR "technology-in-practice")

Annex 3: Extraction Table

Reference	*Abstract*	*Year*	*Country of origin*	*Does the article discuss AI in primary care, in healthcare in general, or any other specific healthcare setting?*	*Type of article/study e.g. original research, review articles, discussions, report. If research or review, qualitative or quantitative?*	*Short summary of content (if Discussion/Whitepapper). PICO (only if empirical)?*	*Most significant findings/conclusions*	*Objective 1A: Do the article themes on inequality match the themes in the conceptual model? Which themes? Give numbers 1-11 as per attached figure. What are the main points?*	*Objective 1B: Does the article introduce any themes on AI and inequalities not covered in the model?*	*Objective 2: Does the article describe how the implementation of AI can affect the patient-doctor relationship, and how this could have implications for healthcare equality?*	*Objective 3: 6.Does the article describe the role of infrastructures, organisational processes and personal involved in implementing an AI system, and how the implementation could affect healthcare equality?*	*Interesting references?*	*Interesting references?*	Added after peer reading?
Leslie, D., et al. (2021). "Does "ai" stand for augmenting inequality in the era of covid-19 healthcare?" The BMJ 372.	Artificial intelligence can help tackle the covid-19 pandemic, but bias and discrimination in its design and deployment risk exacerbating existing health inequity argue David Leslie and colleagues	2021	UK	General Healthcare	Diccussion	Risk of widened inequality in the context of C19 if AI is implemented broader.	Main focus on data representation and societal biases. Interesting point about trust of doctors in system.	9, 10. Bias and underrepresentaon. 3: Trust, but the article focuses on trust of doctors, and how doctors may suspect the AI of being biased and thus mainly use it on "majority" patients.	Trust of doctors, and how doctors may suspect the AI of being biased and thus mainly use it on "majority" patients.		"Cascading" health inequalities through three different mechanisms: Datasets/algorithms, application injustice (only some benefit, widening gap), and power imbalances in problem formulation and agena setting. Illustration! Also useful advise reg			
Abràmoff, M. D., et al. (2020). "Lessons Learned About Autonomous AI: Finding a Safe, Efficacious, and Ethical Path Through the Development Process." American Journal of Ophthalmology 214: 134-142.	Artificial intelligence (AI) describes systems capable of making decisions of high cognitive complexity; autonomous AI systems in healthcare are AI systems that make clinical decisions without human oversight. Such rigorously validated medical diagnostic AI	2020	USA	General healthcare, Primary care (sub discussion reg retinopathy system)	Discussion	Discussion AI ethical issues in ophtamology, focusing on algorithmic bias, privacy and accountability.	Potential to do good if well managed. Discusses importance of not just talk about algorithmic fairness in equality, as this required knowledge of all the degrees of potential impact.	**2:** Increased accessability. **10+11**: Concerns of ethnic and gender bias (refers to Obermeyer): Design so that operations are reduced to scientific characteristics and clinical knowledge rather than proxies (which could be race etc), "algorithmic fairness," or the ability to computationally	No		Very briefly discusses the importance of correct implementation, but no examples or theories.	Challen R, Denny J, Pitt M, Gompels L, Edwards T, TsanevaAtanasova K. Artificial intelligence, bias and	Goodman, S. N., Goel, S., & Cullen, M. R. (2018). Machine learning, health disparities, and causal	
Alami, H., et al. (2020). "Artificial intelligence in health care: Laying the Foundation for Responsible, sustainable, and inclusive innovation in low- And middle-income countries." Globalization and Health 16(1).	The World Health Organization and other institutions are considering Artificial Intelligence (AI) as a technology that can potentially address some health system gaps, especially the reduction of global health inequalities in low- and middle-income countries (LMICs).	2020	Canada	General healthcare	Discussion	AI's potential to improve global health equality, advice for implemention of AI in LMICs.	Five points to maximise benefits and avoid worsening inequalities: 1. Training for all involved in basic AI. 2. Robust monitoring. 3. Contextual needs must be addressed. 4. Proven benefit compared to other interventions such as doctors retention. 5. Inclusive development and	2. Increased availability, affordability. 6. Improved acceptability for stigmatised illness. 9. Underrepresentation in LMIC in datasets. 10. Bias.	Creates risk for intentional ethnic discrimination through proxy-classifying. Risk of medicalising issues that is best addressed through SDH		Importance of community involvemnet and a holistic approach incl SDH to maximise gains and avoid risks.	World Health Organization. Big data and artificial intelligence for achieving universal health coverage: an		
Amann, J., et al. (2020). "Explainability for artificial intelligence in healthcare: a multidisciplinary perspective." BMC Med Inform Decis Mak 20(1): 310.	BACKGROUND: Explainability is one of the most heavily debated topics when it comes to the application of artificial intelligence (AI) in healthcare. Even though AI-driven systems have been shown to outperform humans in certain analytical tasks, the lack of explainability continues to spark	2020	Switzerland	General healthcare	Discussion	Explainability explored from a bioethical perspective. Under *Justice,* there is the case that explainability is necessary for justice	Bias is inevitable, explainability is necessary to mitigate. Also need to make doctors aware of bias risks and subsequent risks of opaque systems.	3. Risk of inequality if trust difference. 10, 11. Bias, risk and need to mitigate,	Strong focus on explainability, as a way to manage bias.	0		Obermeyer Z, Powers B, Vogeli C, Mullainathan S. Dissecting racial bias in an algorithm used to manage the		
Boers, S. N., et al. (2020). "SERIES: eHealth in primary care. Part 2: Exploring the ethical implications of its application in primary care practice." Eur J Gen Pract 26(1): 26-32.	Background: eHealth promises to increase self-management and personalised medicine and improve cost-effectiveness in primary care. Paired with these promises are ethical implications, as eHealth will affect patients' and primary care professionals' (PCPs) experiences, values, norms, and	2020	Netherlands	Primary care	Discussion	Discusses equality and general ethical aspects of eHealth in general, and "personalised digital decision making" i.e. AI.	Risk of disparities increasing due to botth algorithms and differences in usage among different population. General risk of dehumanisation, which is seen as generally negative, but positive reg some sensitive issues.	1 (funtional and physical access,5 and 6 but not specifically equality, 10 (bias).	0	Risk of dehumanisation and pushing responsibility to patients, potentially widening gaps.	Importance of defining the role of the human provider in the system to avoid adverse effects of AI, not specifically equality but more generally quality.	Bodie G, Dutta M. Understanding health literacy for strategic health marketing: eHealth		
Balthazar, P., et al. (2018). "Protecting Your Patients' Interests in the Era of Big Data, Artificial Intelligence, and Predictive Analytics." J Am Coll Radiol 15(3 Pt B): 580-586.	The Hippocratic oath and the Belmont report articulate foundational principles for how physicians interact with patients and research subjects. The increasing use of big data and artificial intelligence techniques demands a re-examination of these principles in light of the	2018	USA	General healthcare	Discussion	Focused on data rights and ethical implications of AI in radiology, but generalisable.	Need for active discussion and frameworks.	1. Digital divide.	Risk of availability bias due to cost. More relevant in private healthcare settings?					
Buch, V. H., et al. (2018). "Artificial intelligence in medicine: Current trends and future possibilities." British Journal of General Practice 68(668): 143-144.	Artificial intelligence (AI) research within medicine is growing rapidly. In 2016, healthcare AI projects attracted more investment than AI projects within any other sector of the global economy.1 However, among the excitement, there is	2018	UK	Primary care	Discussion	What will AI mean for primary care ? It will support Drs, not replace.	Generally very positive, concluding AI's ability to complement on suitable tasks.	2. Increased availability		Improved efficiency.	The biggest hindrance is likely the public perception of AI in medicine. Thus incremental that Drs remain in control.			
Bigman, Y. E., et al. (2021). "Threat of racial and economic inequality increases preference for algorithm decision-making." Computers in Human Behavior 122.	Artificial intelligence (AI) algorithms hold promise to reduce inequalities across race and socioeconomic status. One of the most important domains of racial and economic inequalities is medical outcomes; Black and low-income people are more likely to die from many diseases.	2021	USA	General healthcare	Quantitative	P: mTurk in US and Korea. I: Treat of inequality in treatment - choice of AI or doctors. C: No threat. O: Amount chosing to have an AI decide their care. Asked pupils in Korea and mTurk in US on wether they would want to see an AI or a doctor in a hospital triage. Interventions was to introduce a	Threat of inequality increases acceptability of AI. Black americans more keen for AI after treat compared to white.	11. Less risk. 10. Risk of bias, but less than humans! 4. More trustworthy! 3. Equal trustworthyness initially, no worse for Black.	0		Threat of current inequality makes patients more accepting of AI.	Lai, M. C., Brian, M., & Mamzer, M. F. (2020). Perceptions of artificial intelligence in healthcare: findings from		
Clark, C. R., et al. (2021). "Health Care Equity in the Use of Advanced Analytics and Artificial Intelligence Technologies in Primary Care." J Gen Intern Med 36(10): 3188-3193.	The integration of advanced analytics and artificial intelligence (AI) technologies into the practice of medicine holds much promise. Yet, the opportunity to leverage these tools carries with it an equal responsibility to ensure that principles of equity are incorporated into their	2021	USA	Primary care	Discussion	Importance of GP in general to consider SDH, and a general lack of SDH data collected in GP. Inequalites goes beyond healthcare and should be addressed accordingly. All AIs should be evaluated for equality also with regards to access and not only accuracy. Pro-equality		1, 2. 9, 10, 11.	Diffusely focuses on having an equality perspective beyond the algorithms, and to focus on SDHs with the help of AI in PC.		Diffusely focuses on having an equality perspective beyond the algorithms, and to focus on SDHs with the help of AI in PC.	Matheny ME, Thadaney Israni S, Ahmed M, Whicher D. AI in Health Care: The Hope, the Hype, the		
Coiera, E. (2019). "The Price of Artificial Intelligence." Yearbook of medical informatics 28(1): 14-15.	INTRODUCTION: Whilst general artificial intelligence (AI) is yet to appear, today's narrow AI is already good enough to transform much of healthcare over the next two decades. OBJECTIVE: There is much discussion of the potential benefits of AI in healthcare and this paper reviews the cost that	2019	Australia	General Healthcare	Discussion	Summarises issues with AI in medicine.	AI is narrow. May help simple quick patients more.	1. Lower functional access for disadvantaged populations. 5. Dehumanisation/medicalisation worse for complex patients.			The most demanding and influential patients are young and healthy, and are likely to push for AI. "To not engange [in the transformation] is to pay the highest price"	Marshall M, Shah R, Stokes Lampard H. Online consulting in general practice: making the move from		
Embi, P. J. (2021). "Algorithmovigilance - Advancing Methods to Analyze and Monitor Artificial Intelligence-Driven Health Care for Effectiveness and Equity." JAMA Network Open 4(4).	In recent years, there has been rapid growth and expansion in the use of machine learning and other artificial intelligence approaches applied to increasingly rich and accessible health data sets to develop algorithms that guide and support health care.1 As they make their way into practice, such	2021	USA	General Healthcare	Discussion	Refers to another article, discusses three different ways of debiasing an algorithm predicting post-partum depression. I predicts more in White than black women, due to societal bias.	Debiasing studies very important.	10, 11. Bias and debiasing.			Emphasises the importance of careful implementation, no details	Park Y, Hu J, Singh M, et al. Comparison of methods to reduce bias from clinical prediction models of postpartum		
Ferryman, K. (2020). "Addressing health disparities in the Food and Drug Administration's artificial intelligence and machine learning regulatory framework." Journal of the American Medical Informatics Association 27(12): 2016-2019.	The exponential growth of health data from devices, health applications, and electronic health records coupled with the development of data analysis tools such as machine learning offer opportunities to leverage these data to mitigate health disparities. However, these tools	2020	USA	Generarl Healthcare	Discussion	Recommendations to FDA on updated, more holistic equity review processes for new products.	The actual usage of the AI system affects equality as well - a system can be chosen to be implemented only of disadvantaged groups, for example, in order to reduce disparities.				Risk of over-emphaisis on agility reg regulation, due to the fast rate of development and change.	Chen IY, Szolovits P, Ghassemi M. Can AI help reduce disparities in general medical and mental health		
Cave, S., et al. (2021). "Using AI ethically to tackle covid-19." Bmj 372: n364.	Taking a principled approach is crucial to the successful use of AI in pandemic management, say Stephen Cave and colleagues	2021	UK	General healthcare	Discussion	Discussed AI in the context of C19 but expanding into AI in general.	Benefits and challanges - AI can be good but needs caution.	1. Digital divide. 2. Increased availability. 3. Distrust among historically discriminated groups. 9. Underrepresentation. 10. Underlying bias.				Veinot TC, Mitchell H, Ancker JS. Good intentions are not enough: how informatics interventions		
Blease, C., et al. (2018). "Computerization and the future of primary care: A survey of general practitioners in the UK." PLoS One 13(12): e0207418.	OBJECTIVE: To describe the opinions of British general practitioners regarding the potential of future technology to replace key tasks carried out in primary care. DESIGN: Cross sectional online survey. PARTICIPANTS: 1,474 registered GPs in the United Kingdom. MAIN	2018	UK	Primary care	Quantitative	Survey of GPs reg what tasks in GP they think will be replaced by AI in the future, and timescale.	Mostly administrative tasks. Very few (5.6 %) though AI could replace GPs empathy. Diagnosis and prognosis was the two most "AI-likely" tasks. Also "However, as leading informaticians caution, cycles ofhype camouflage broader historical trends: Amara's Law is the observation that we tend to	No	No	The article implies that a partial or total replacement of GPs with AI for certain tasks requiring empathy would result in reduced quality, if done. NB that GPs are not AI experts.				
Blease, C., et al. (2019). "Artificial intelligence and the future of primary care: exploratory qualitative study of UK general practitioners' views." Journal of Medical Internet Research 21(3).	BACKGROUND: The potential for machine learning to disrupt the medical profession is the subject of ongoing debate within biomedical informatics and related fields. OBJECTIVE: This study aimed to explore general practitioners' (GPs') opinions about the potential impact of	2019	UK	Primary care	Qualitative	P: 66 GPs in UK. I: hypothetical replacement of GPs on 6 different primary care tasks, limitations and benefits. C:0 O: GPs viws as limitations, benefits and ethical concerns.	Limiatations and concerns focused on lack of patient-centreness and empathy, non-verbal cues. No GPs mentioned bias.	5. dehumanisation. 2. availability positively impacted.		General sceptisim. GPs do not mention bias.	Effective implementation may be hindered by current high workload of GPs.	Blease C, Bernstein MH, Gaab J, Kaptchuk TJ, Kossowsky J, Mandl KD, et al. Computerization and the		

Cirillo, D., et al. (2020). "Sex and gender differences and biases in artificial intelligence for biomedicine and healthcare." npj Digital Medicine 3(1).	Precision Medicine implies a deep understanding of inter-individual differences in health and disease that are due to genetic and environmental factors. To acquire such understanding there is a need for the implementation of different types of technologies based on artificial intelligence (AI)	2020	Spain	General healthcare	Review	Lists several kinds of intrisic bias, but also underscores the opportunity of AI to include "wanted" bias.	Distinguish between desirable and undesirable bias. Explainable algorithms.	9 underrepresentation, 10 underlying bias, 11 opportunity to introduce desirable bias				Can, A. I. Help reduce disparities in general medical and mental health care? AMA J. Ethics 21, E167–E179		
Holford, W. D. (2020). "The repression of métis within digital organizations." Prometheus 36(3): 253-276.	[Numerous organizations are placing great emphasis on such techniques as evidence-based protocols to automation and artificial intelligence (AI) with the aim of improving efficiency and maximizing profitability. Such instrumental techniques attempt to formalize all manner of	2020	Canada	General	Discussion	Digital technology represses "metis", which is a loss for the setting they are applied in.	When something that used to include human skills is digitalised, "metis" gets repressed; nuances and intuition is very hard or impossible to translate straight to computer systems and AI. This "truncates knowledge" and is a threat to personalised and compassionate care.			AI can not outright replace humans without a loss of quality, merely complement.	AI can not outright replace humans without a loss of quality, merely complement.			
Blease, C., et al. (2020). "US primary care in 2029: A Delphi survey on the impact of machine learning." PLoS One 15(10 October).	OBJECTIVE: To solicit leading health informaticians' predictions about the impact of AI/ML on primary care in the US in 2029. DESIGN: A three-round online modified Delphi poll. PARTICIPANTS: Twenty-nine leading health informaticians. METHODS: In September 2019,	2020	USA	Primary care	Qualitative	P: 16 health informaticians. I: Impact on patient care, acc, workforce and long-term future for GPs. C: 0 O: Delphi	Informaticians are here generally very positive	2. Increased availability by amounts. However risk for divide due to cost. 11. Less bias.	Risk of availability bias due to cost. More relevant in private healthcare settings? More, empathy, for undisclosed reasons.	2029 AI will affect GPs a lot, but they will notbe replaced.	One participant predicted that doctors will have to learn more informatics to be able to properly manage AI.	Doraiswamy PM, Blease C, Bodner K. Artificial intelligence and the future of psychiatry: Insights from a global		
Holzmeyer, C. (2021). "Beyond 'AI for Social Good' (AI4SG): social transformations—not tech-fixes—for health equity." Interdisciplinary Science Reviews 46(1-2): 94-125.	This paper reflects on proliferating AI for Social Good (AI4SG) initiatives, with an eye to public health and health equity. It notes that many AI4SG initiatives are shaped by the same corporate entities that incubate AI technologies, beyond democratic control, and stand to profit	2021	USA	General healthcare	Discussion	Risks of AI hype in society and health	Precision medicine can take focus from equality-wise more important public health interventions and social care. Also risk for bias in data.	10. Bias. 1. Digital divide and cost	Focusing on narrow interventions instead of upstream sources of inequality.		As mentioned, risk of AI being "precision medicine focused" , which is inherently prone to inequalities, compared to public health applicaitons. For example, "what if US scientific, health and business leaders were equally or more enthusiastic about acting on current research			
Cordeiro, J. V. (2021). "Digital Technologies and Data Science as Health Enablers: An Outline of Appealing Promises and Compelling Ethical, Legal, and Social Challenges." Frontiers in Medicine 8.	Digital technologies and data science have laid down the promise to revolutionize healthcare by transforming the way health and disease are analyzed and managed in the future. Digital health applications in healthcare include telemedicine, electronic health	2021	Portugal	General Healthcare	Review, narrative	Summarises issues with AI in medicine.	Various points along ethical principles. Trust, fairness and dehumanisation important themes.	1. Lower functional access for disadvantaged populations, but 2: more availabilty. 5. Dehumanisation/medicalisation worse for complex patients. 9, 10, 11: Risk for bias in datasets, but opportunity to visualise and mitigate.				McAuley A. Digital health interventions: widening access or widening inequalities? Public Health. (2014)		
Keyes, O., et al. (2021). "Truth from the machine: artificial intelligence and the materialization of identity." Interdisciplinary Science Reviews 46(1-2): 158-175.	Critics now articulate their worries about the technologies, social practices and mythologies that comprise Artificial Intelligence (AI) in many domains. In this paper, we investigate the intersection of two domains of criticism: identity and scientific knowledge. On one hand, critics of AI in public policy	2021	USA	General	Discussion	Keyes et al (5) set out to describe the relation between AI and identity, and as part of that the relations between AI and scientific studies. They theorise that AI, as a consequence of both "mythology" and the black-box dilemma of deep-learning systems, may be seen as an objective truth, as such	Risk that AI is seen as objective truth due to both black box and mythology. This may lead to false assumptions of causaton and ignosing the social context. Autism's correlation with genes is taken as an example .	5, (but does not discuss equality)			Tricky one to read this!			
Deferio, J. J., et al. (2019). "Social determinants of health in mental health care and research: a case for greater inclusion." J Am Med Inform Assoc 26(8-9): 895-899.	Social determinants of health (SDOH) are known to influence mental health outcomes, which are independent risk factors for poor health status and physical illness. Currently, however, existing SDOH data collection methods are ad hoc and inadequate, and SDOH data are	2019	USA	General Healthcare	Discussion	The case for AI-tools to extract socioeconomic data	AI can improve access to psychiatric care thorugh identifying low SES, enabling targeted interventions.		The ability to highlight general socioeconomic drivers of poor health, and target interventions.					
Kottler, N. (2020). "Artificial Intelligence: A Private Practice Perspective." J Am Coll Radiol 17(11): 1398-1404.	Artificial intelligence (AI) is an exciting technology that can transform the practice of radiology. However, radiology AI is still immature with limited adopters, dominated by academic institutions, and few use cases in general practice. With scale and a focus on innovation, our practice	2020	USA	Radiology	Discussion	Experiences from a private radiology company who is using AI	Close contact with stakeholders important for acceptability and adoption. Clear feedback system to developers important to keep trust and engagement.	2: increased capacity. 9, 10 11, bias in datasets.	no	No	Implementation needs to be done in close contact with stakeholders. In this case, the importance of involving radiologists in the implementation and choise of AI-tasks was improtant for acceptabilty.			
Fejerskov, A. M. (2021). "Algorithmic Bias and the (False) Promise of Numbers." Global Policy 12(56): 101-103.	Advances in AI and machine learning systems have given rise to a contemporary euphoria of progress. This commentary discusses the challenges posed by advances in artificial intelligence, or more precisely the increasing usage of algorithmic systems, in global health, sometimes carried	2021	Denmark	General Healthcare	Discussion	Bias is complex and multifactoral.	Transperancy is not just a data question, it is also a question of business secrets - it's not all in the code.	10, 11.						
Maitland, S., et al. (2020). "AI: simply reinforcing medicine's worst biases?" BMJ Innovations 6(4): 117-120.	Introduction The emergence of Machine Learning (ML), the application of the more general field of Artificial Intelligence, to automate statistical inference to detect patterns in data, has opened up entire new domains of complex data analysis. This is especially	2020	UK	General Healthcare	Discussion	Focus on algorithmic bias, no system effects.	Risk of bias from data, need to properly evaluate systems in various socioeconomic settings, ensure social data is being captured to allow evaluation.	9,10,11.	Risk of confirmation bias: we trust the AI when it says what we want but not when it doesnt.	No	Need for testing in real-life socioeconomically diverse areas to ensure no biases.	Academy of Medical Royal Colleges. Artifical Intelligence in Healthcare [Internet]. 2019 [cited 2019 May 9].		
Marshall, M., et al. (2018). "Online consulting in general practice: making the move from disruptive innovation to mainstream service." Bmj 360: k1195.		2018	UK	Primary care	Discussion	Written by the leadership of RCGP on risk of disruption from eHealth (not specifically AI, mainly remote in some way)>	Risk of cherry picking and undermining the current funding system. On the , other hand, change to increase accessability and acceptability. Could also free up resources.	1, 2, 5, 6,			Importance of finding the right application for new interventions with a system perspective.			
Martinez-Martin, N., et al. (2021). "Ethical issues in using ambient intelligence in health-care settings." Lancet Digit Health 3(2): e115-e123.	Ambient intelligence is increasingly finding applications in health-care settings, such as helping to ensure clinician and patient safety by monitoring staff compliance with clinical best practices or relieving staff of burdensome documentation tasks. Ambient intelligence	2021	USA	General Healthcare	Discussion	Ambient intelligence; a subset of AI continiusly monitoring data in health settings "from the outside". Lots of focus on privacy issues specific to ambient monitoring.	From an equality point-of-view: Bias may come all the normal ways but also from the people labelling and developing the datasets - important to keep a diverse workforce there to avoid skewed perceptions of "normality".	9, 10.	Risk of skewed percepetion of "normality" if developers and evaluaters concist of homogenous groups. Related to 10, hideen biasses.		Implemtation needs to be done with an equality perspective, as there is a risk of only benefitting the already well off.			
Chen, I. Y., et al. (2019). "Can AI help reduce disparities in general medical and mental health care?" AMA journal of ethics 21(2): 167-179.	Abstract Background: As machine learning becomes increasingly common in health care applications, concerns have been raised about bias in these systems' data, algorithms, and recommendations. Simply put, as health care improves for some, it might not improve for all.	2019	USA	Psychiatry	Quantitative	Ethnicity, socioeconomic and gender data compared when modelling ICU mortality and psych readmission probability on free-text data.	More accurate for white men. Predicts (rightly, but biased?) higher mortality for ethnic minorities and women.	9, 10.	No					
Moreau, J. T., et al. (2020). "Biased intelligence: on the subjectivity of digital objectivity." BMJ Health Care Inform 27(3).		2020	Canada	General Healthcare	Discussion	Unequal distribution of both AI development, research and sampling.	Big opportunities also for improving availability and lowering costs, but needs to be promoted more equally, both geogpraphically and socioeconomically. For example, "GP at hand" catering to well-off, young patients.	2, increased availability/lowered cost. 5. Worse for socially complex patients. 9, 10. Bias and underrepresentation.			Human-centred AI is key to ensure equal AI, from production to implementation. See reference #2 here to the right	Sujan M, Furniss D, Grundy K, et al. Human factors challenges for the safe use of artificial intelligence in	Riedl MO. Human-centered artificial intelligence and machine learning. Hum Behav Emerg Technol 2019;1:33–6.	
Nordling, L. (2019). "A fairer way forward for AI in health care." Nature 573(7775): S103-S105.	Without careful implementation, artificial intelligence could widen health-care inequality. [Figure not available: see fulltext.]. © 2019, Nature.	2019	South Africa	General Healthcare	Discussion	Focus on bias, discussed Obermeyer's findings among other	Important to mainstream equity throughout the whole development and implementation process, including both datasets and evaluation.	9,10,11. 1: increased availability in low-cost settings possible.	In unequal societies, AI may only benefit the rich. E.g. you need an X-ray machine to be able to use AI for X-ray analysis.		Mentions the need to locally anchor initiatives to avoid unexpected biases due to surrounding infrastructure, particulary reg LMICs	Ferryman, K. (2020). Addressing health disparities in the Food and Drug Administration's artificial		
Pagliari, C. (2021). "Digital health and primary care: Past, pandemic and prospects." J Glob Health 11: 01005.	This article reflects on the breadth of digital developments seen in primary care over time, as well as the rapid and significant changes prompted by the COVID-19 crisis. Recent research and experience have shone further light on factors influencing the implementation and usefulness of these	2021	UK	Primary care	Discussion			1, 2. 3 (but no equality). 9, 10.			If AI systems are not implemented in an efficient way together with GPs/HCPs, they may increase workload and take resources rather than the other way around, as GPs have to double check and/or fix mistakes.			

Hernandez-Boussard, T., et al. (2020). "MINIMAR (MINimum Information for Medical AI Reporting): Developing reporting standards for artificial intelligence in health care." Journal of the American Medical Informatics Association 27(12): 2011-2015.	The rise of digital data and computing power have contributed to significant advancements in artificial intelligence (AI), leading to the use of classification and prediction models in health care to enhance clinical decision-making for diagnosis, treatment and	2020	USA	General healthcare	Framework	Reporting standard for AI in medicine: MINIMAR	Focus on bias in algorithms: population behind training data incl demographics, ethnicity and socioeconomy, evaluation methods incl external evaluation.	9, 10.. No focus on external effects, only "Intrinsic".						
Prabhakaran, V. and D. Martin (2020). "Participatory Machine Learning Using Community-Based System Dynamics." Health and Human Rights 22(2): 71-74.	The pervasive digitization of health data, aided with advancements in machine learning (ML) techniques, has triggered an exponential growth in the research and development of ML applications in health, especially in areas such as drug discovery, clinical diagnosis, and	2020	USA	General healthcare	Discussion	Promoting participatory methods to advance fairness in AI.	Own method "Community-Based-System Dynamics", CBSD, to facilitate development, see references	0	Without focusing on specifics, they recommend a community-focus approach for equality		Discussing causal chains that lead to false problem formulations: such as that healthcare costs are equivalent to need (Obermeyer). Advises community engagement using CBSD (reference to right).		D. Martin Jr., V. Prabhakaran, J. Kuhlberg, et al., "Participatory problem formulation for fairer	
Rajkomar, A., et al. (2018). "Ensuring Fairness in Machine Learning to Advance Health Equity." Ann Intern Med 169(12): 866-872.	Machine learning is used increasingly in clinical care to improve diagnosis, treatment selection, and health system efficiency. Because machine-learning models learn from historically collected data, populations that have experienced human and structural biases in	2018	USA	General Healthcare	Discussion	Different ways of defining fairness (this needs a whole section, and perhaps inclusion in the interviews). Equal outcome (gold standard, but how?), equal performance (easy but narrow), equal allocation (one step more "advanced" than equal performance since it disregards	Models should be tested for both equal allocation and equal performance, and discrepancies be discussed and potentially mitigated. Also explicit recommendation not to have "colour or gender blind" algorithms.	10, 11 Bias and opportunity to improve			Privilege bias: Models may be unavailable in settings where protected groups receive care or require technology/sensors disproportionately available to the nonprotected class Informed mistrust: Given historical exploitation and unethical practices, protected			
Smith, M., et al. (2021). "From Code to Bedside: Implementing Artificial Intelligence Using Quality Improvement Methods." J Gen Intern Med 36(4): 1061-1066.	Despite increasing interest in how artificial intelligence (AI) can augment and improve healthcare delivery, the development of new AI models continues to outpace adoption in existing healthcare processes. Integration is difficult because current approaches separate the development of AI	2021	USA	General healthcare	Discussion	How to use implementaion sicience methods (the PDSA cycle) to integrate AI into medicine, used a mixed-methods approach. Currently applications are developed away from the clinical setting and may thus lack a clear user case or not function in the complexity that is a clinical	A common problem is prioritising AI over the problem it is supposed to solve: Is AI needed?	9, 10, Biases and opportunit to mitigate			Again focuses on the importance of basing the AI on a concrete tangible problem that needs to be solved, and not the other way around. Plan - do - study - adjust. In the two last steps, use both quant markers for success and interviews with stakeholders. (PDSA)			
Karches, K. E. (2018). "Against the iDoctor: why artificial intelligence should not replace physician judgment." Theoretical Medicine and Bioethics 39(2): 91-110.	Experts in medical informatics have argued for the incorporation of ever more machine-learning algorithms into medical care. As artificial intelligence (AI) research advances, such technologies raise the possibility of an "iDoctor," a machine theoretically capable of replacing the judgment of primary	2018	USA	Primary care	Discussion	Discusses why AI should not and can not replace humans in primary care.	Lack of individualisation, lack of compassion, lack of ability to work with the patient and let the patient be the teacher.	57 Dehumanisation. No explicit equality focus.		Main point of the article: AI can't and shouldn't replace doctors in primary care due to the fundamental patient-focused role of GPs.				
Kerr, D. and D. C. Klonoff (2019). "Digital Diabetes Data and Artificial Intelligence: A Time for Humility Not Hubris." J Diabetes Sci Technol 13(1): 123-127.	In the future artificial intelligence (AI) will have the potential to improve outcomes diabetes care. With the creation of new sensors for physiological monitoring sensors and the introduction of smart insulin pens, novel data relationships based on personal phenotypic and genotypic	2018	USA	Diabetes	Discussion	On equality risks with diabetes data and AI applications. *The quantitative fallacy* . On example is if someone has a hypoglycemic event, and the AI is unable to understand the social, "soft" reasons behind this, and thus changes medication/	Continuity of care is associated with better diabetes outcomes - not easily measureable but still true!	9, underrepresentation. 7. Agency for self-care (although not explicit, the article does discuss how socioeconomy changes beliefs in diabetes and diabetes management, and that AI likely would fail to grasp that if "one-size fits all" based on just quant data).						
Arun, C. (2019). "AI and the Global South: Designing for Other Worlds."	This chapter is about the ways in which AI affects, and will continue to affect, the Global South. It highlights why the design and deployment of AI in the South should concern us. Towards this, it discusses what is meant by the South. The term has a history connected with the	2019	UK	General society	Discussion/Book chapter	Examples of ways AI affects equality of various kinds in developing countries. Global south does in some contexts also denote immigrants to "the north". Facebook in Myanmar: Lack on established media and diverse and unequal population led to hate speech and discrimination:	Several issues: Implementation problem (e.g. Facebook), bias in data combined with a lack of questioning the results from doctors and public, and a lack of diversity in development and implementation organisations allowing all this to happen.	9, 10. 1 (in the case of access to care in India)			Facebook in Myanmar: Lack on established media and diverse and unequal population led to hate speech and discrimination: Facebook worked even worse than in the west!			
Mema, E. and G. McGinty (2020). "The Role of Artificial Intelligence in Understanding and Addressing Disparities in Breast Cancer Outcomes." Current Breast Cancer Reports 12(3): 168-174.	Purpose of Review: The goal of our paper is to explore the role of AI in understanding health disparities in cancer care and its potential role in resolving them. Recent Findings: Multiple studies have shown that with the recent advances in AI, its integration in cancer care has the potential to	2020	USA	Oncology/breast cancer	Review, narrative	Goes through mechanisms for current inequality and looks at Ais effect on them.	Example of bias: low SES have worse prognosis, thus the AI may chose to not give them chemo, further worsening inequalities. AI can work against this, flagging inappropriate Tx decisions (?)	2, 9, 10, 11				Zou J, Schiebinger L. AI can be sexist and racist - it's time to make it fair. Nature. 2018;559(7714):324–6.		
Dankwa-Mullan, I., et al. (2021). "A proposed framework on integrating health equity and racial justice into the artificial intelligence development lifecycle." Journal of Health Care for the Poor and Underserved 32(2): 300-317.	The COVID-19 pandemic has created multiple opportunities to deploy artificial intelligence (AI)-driven tools and applied interventions to understand, mitigate, and manage the pandemic and its consequences. The disproportionate impact of COVID-19 on racial/ ethnic	2021	USA	General Healthcare	Discussion/framework	Recommendations to integrate health equity into AI development. Framework included. Good framework and introduction!	Important to start by analysing existing inequalities and define desired end-targets (such as equality in blood pressure) together with affected groups.	9, 10, 11 - all intrinsic. Also risk of dehumanisation, 5.			Importance of community perspective and stakeholder consultations to ensure equity in implementation.	14. Roosli E, Rice B, Hernandez-Boussard T. Bias at warp speed: how ai may contribute to the disparities		
Christopher, M., et al. (2020). "Effects of study population, labeling and training on glaucoma detection using deep learning algorithms." Translational Vision Science and Technology 9(2): 1-14.	Purpose: To compare performance of independently developed deep learning algorithms for detecting glaucoma from fundus photographs and to evaluate strategies for incorporating new data into models. Methods: Two fundus photograph datasets from the	2020	Japan	Ophtalmology	Quantatative	Two different datasets with different populations was trained to detect glaucoma, then tested on independent, multiethnic datasets.	Retraining of models important for different populations, but can be done reliably in this setting.	9. Underrepresentation.						
Shaw, J., et al. (2019). "Artificial Intelligence and the Implementation Challenge." J Med Internet Res 21(7): e13659.	BACKGROUND: Applications of artificial intelligence (AI) in health care have garnered much attention in recent years, but the implementation issues posed by AI have not been substantially addressed. OBJECTIVE: In this paper, we have focused on machine learning (ML) as a form	2019	Canada	General healthcare	Discussion/framework	Using the NASSS framework for implementation analysis, looks at AI as either decision support or automation.	This is a great source of reference, on AI and on implementation issues, if not not specifically on inequality.	Brief mention of bias issues (9, 10) as a barrier to implementability.			AI needs to add value - simple decision support may not add much value in a clinical setting, but rather visualising complex correlations may be more useful. Explainability is closely related to trust: poor implementation may result if AI is not explainable.			
Lin, S. Y., et al. (2019). "Ten Ways Artificial Intelligence Will Transform Primary Care." Journal of General Internal Medicine 34(8): 1626-1630.	Artificial intelligence (AI) is poised as a transformational force in healthcare. This paper presents a current environmental scan, through the eyes of primary care physicians, of the top ten ways AI will impact primary care and its key stakeholders. We discuss ten distinct problem spaces and the	2019	USA	Primary care	Discussion	Focus on performance and workforce rather than equality.	AI needs to complement rather than replace GPs - the focus here is on GP's being able to keep their humanity.	No		AI needs to complement rather than replace GPs - the focus here is on GP's being able to keep their humanity		Israni ST, Verghese A. Humanizing Artificial Intelligence. JAMA. 2019;321(1):29–30.		
Veinot, T. C., et al. (2018). "Good intentions are not enough: how informatics interventions can worsen inequality." Journal of the American Medical Informatics Association 25(8): 1080-1088.	Health informatics interventions are designed to help people avoid, recover from, or cope with disease and disability, or to improve the quality and safety of healthcare. Unfortunately, they pose a risk of producing intervention-generated inequalities (IGI) by disproportionately benefiting	2018	USA	General healthcare	Discussion/narrative review	Outlines ways informatics can worsen inequalities. Important framework connected to AAAQ.	Baseline, access, uptake, adherence, effectiveness	Access: 1, 2. Uptake: 3. Distrust along ethnic lines. Adherence: 7. Less agency for change when self-care involved. Effectiveness: 7. Also 9, 10 (bias).			Strong focus on inclusive design of interventions rather than implementation. Also mentions imporatance of evaluating and monitoring for socioeconomic inequality, which in turn neccesites that these demographics are recorded in the first place.			
Clark, C. R., et al. (2021). "Predicting Self-Rated Health Across the Life Course: Health Equity Insights from Machine Learning Models." J Gen Intern Med 36(5): 1181-1188.	BACKGROUND: Self-rated health is a strong predictor of mortality and morbidity. Machine learning techniques may provide insights into which of the multifaceted contributors to self-rated health are key drivers in diverse groups. OBJECTIVE: We used machine learning algorithms to predict self-	2021	USA	General Healthcare	Quantitative	(500000+500000) persons over two years, used AI to predict self-rated health based on social and behavioural reported factors.	Equal predicon for different groups, but helped identify socioeconomic drivers of perclevied ill-healht	0	The ability to highlight general socioeconomic drivers of poor health, and target interventions.			Lin SY, Mahoney MR, Sinsky CA. Ten ways artificial intelligence will transform primary care. J Gen Intern Med.		
Gao, Y. and Y. Cui (2020). "Deep transfer learning for reducing health care disparities arising from biomedical data inequality." Nature Communications 11(1).	As artificial intelligence (AI) is increasingly applied to biomedical research and clinical decisions, developing unbiased AI models that work equally well for all ethnic groups is of crucial importance to health disparity prevention and reduction. However, the biomedical data	2020	USA	General healthcare	Quantitative		Vast majority of cancer genomics data (91 %) from caucasians. "Transfer learning" instead of "mixed learning" given more equal algorithms on such datasets.	9, underrepresentation						
Martin Jr, D., et al. (2020). "Participatory problem formulation for fairer machine learning through community based system dynamics." arXiv preprint arXiv:2005.07572.		2020	USA	General healthcare	Discussion	Introduces "community-based system dynamics"/CBSD as a way to create a more represntative problem formulation (really a theory of change), and thus build fairer AI. Compares with Obermeyer example of a non-participatory problem formulation.		10, 11.	Focus on "problem formulation", could be a new one, could also be 10?			Jean-Francois Trani, Ellis Ballard, Parul Bakhshi, and Peter Hovmand. Community based system dynamic as an		

Goetz, C. M., et al. (2020). "Perceptions of virtual primary care physicians: A focus group study of medical and data science graduate students." PLoS One 15(12 December).	BACKGROUND: Artificial and virtual technologies in healthcare have advanced rapidly, and healthcare systems have been adapting care accordingly. An intriguing new development is the virtual physician, which can diagnose and treat patients independently. METHODS AND	2020	Italy	Primary care	Qualitative	Interviews w med- and engineering students on general thoughs of virtual primary care (e.g. AI driven)	Generally positive, acknowledges that mainly convenient for young and healthy patients. Insufficient for complex psychosocial needs.	2. Availability better. 4. More fair. 5 Worse for complex patients. 6. Less stigma.			Students emphaisise that AI should not become a low-cost alternative to in-person care.	Razzaki S, Baker A, Perov Y, Middleton K, Baxter J, Mullarkey D, et al. A comparative study of		
Hendrix, N., et al. (2021). "Artificial intelligence in breast cancer screening: primary care provider preferences." Journal of the American Medical Informatics Association : JAMIA 28(6): 1117-1124.	BACKGROUND: Artificial intelligence (AI) is increasingly being proposed for use in medicine, including breast cancer screening (BCS). Little is known, however, about referring primary care providers' (PCPs') preferences for this technology. METHODS: We identified the most important	2021	USA	Primary care	Quantitative	91 GPs ranked attributes important for breast cancer screening AI, through chosing between made-up products with varying properties.	Sensitivity, transperance and diversity of training data was in order the three most important factors. GPs generally positive about this kind of application.	9, underrepresentation			GPs generally positive to this, but wants radiologists to be accountable and "in-the-loop" for their own acceptability.			
McCartney, M. (2017). "General practice can't just exclude sick people." BMJ: British Medical Journal 359.		2017	UK	Primary care	Discussion	Reg Babylon Health and "GP at hand"	AI is being used to reap easy money for easy patients, whilst difficult patients are being left behind (or have less money left)	1. Digital divide 5. Worse for complex patients.	System-wide effects of switching resources to easy, young, IT-litterate patients.					
McCradden, M. D., et al. (2020). "Patient safety and quality improvement: Ethical principles for a regulatory approach to bias in healthcare machine learning." Journal of the American Medical Informatics Association 27(12): 2024-2027.	Accumulating evidence demonstrates the impact of bias that reflects social inequality on the performance of machine learning (ML) models in health care. Given their intended placement within healthcare decision making more broadly, ML tools require attention to	2020	USA	General Healthcare	Discussion	Recommendations for evaluation of AI systems, ethics	Need to record protected characteristics when doing datasets, to be able to analyse for bias. Auditing of products for reliability for target audience, systemic effects, ongoing monitoring to reduce risk of worsening bias-loops.	9. Underrepresentation. 10. Hidden bias.	Risk of bias in AI to be worse than human bias as it may be percieved as "objective" and thus uncritically acted upon.			Chen IY, Szolovits P, Ghassemi M. Can AI help reduce disparities in general medical and mental health	Oakden-Rayner L, Dunnmon J, Carneiro G, Ré C. Hidden stratification causes clinically meaningful	
Morley, J., et al. (2020). "The ethics of AI in health care: A mapping review." Soc Sci Med 260: 113172.	This article presents a mapping review of the literature concerning the ethics of artificial intelligence (AI) in health care. The goal of this review is to summarise current debates and identify open questions for future research. Five literature databases were searched to support the following	2020	UK	General Healthcare	Review, narrative	Listing ethical concerns with AI in healthcare. Explicitly focused on issues unique to AI. A comprehensive review of 156 papers on AI in healthcare-ethics.	Divides ethical issues by "epistemic", "normative", and "overarching", and by level (individual - interpersonal - group - society etc.). Acting on AI for a patient includeds gaining knowledge (AI telling them), awareness/reflection and action, all which potentially poses	7. AI may push responsibility from PCPs patients, putting the blame for poor outcomes on the patients "poor usage".	Not only is the algorithm opaque, the whole chain of actors and event behind and AI decision is very complex.					
Lal, M.-C., et al. (2020). "Perceptions of artificial intelligence in healthcare: findings from a qualitative survey study among actors in France." Journal of translational medicine 18(1): 1-13.	Background Artificial intelligence (AI), with its seemingly limitless power, holds the promise to truly revolutionize patient healthcare. However, the discourse carried out in public does not always correlate with the actual impact. Thus, we aimed to obtain both an overview of how	2020	France	General Healthcare	Qualitative	Interviewed various stakeholders (not including patients) on how AI will affect healthcare and the doctor-patient relation.	Most doctors were sceptical about how much AI would impact practice. Does not elaborate on patinet-doctor relationship. Concerns about accountability.							
Miller, S., et al. (2020). "Patients⇔ utilization and perception of an artificial intelligence‐based symptom assessment and advice technology in a British primary care waiting room: Exploratory pilot study." JMIR Human Factors 7(3).	BACKGROUND: When someone needs to know whether and when to seek medical attention, there are a range of options to consider. Each will have consequences for the individual (primarily considering trust, convenience, usefulness, and opportunity costs) and for the wider health system	2020	UK	Primary care	Qualitative	523 patients chose to participate in a trial of ADA, a triage bot. Answered survey afterwards.	63% of patients claimed the app reduced their GP visits. The vast majority of participating patients was under 50, and younger patients also found it more beneficial and more likely to change their decision on care level. (22 % of under 24, 0 % of over 70).	The article does not discuss equity as such, but clearly touches on 1 and 5: Digital divide and risk for unequal benefit to easy patients. This also connects to system-wide effects i.e. resource drain.		Patients were generally very postive, mainly relating to accessibility. "Although speculative, the fact that older people found the app just as easy to use but reported less engagement might suggest that the issue is not one of usability or familiarity with technology.	" It also became clear that patients often misspelled. We worked with our product team to address this issue, and Ada is now able to recognize and automatically correct a wide range of incorrectly spelt terms."	1. Torjesen I. Patients find GP online services "cumbersome ," survey finds. BMJ 2019 Jul 22;366:l4800.		
Murphy, K., et al. (2021). "Artificial intelligence for good health: a scoping review of the ethics literature." BMC Medical Ethics 22(1).	BACKGROUND: Artificial intelligence (AI) has been described as the "fourth industrial revolution" with transformative and global implications, including in healthcare, public health, and global health. AI approaches hold promise for improving health systems worldwide, as well as	2021	Canada	General Healthcare	Review, narrative	Four ethical themes: Accountability, trust, bias and privacy.	Noted assymetry in previous research with focus on clinical medicine and less on public health and society-wide effects.	9, 10. Bias and underrepresentain. 7. AI may increase inequalities due to commonly pushing self-management				Corbett J, d'Angelo C, Gangitano L, Freeman J. Future of health: findings from a survey of stakeholders		
Skorburg, J. A. and J. Yam (2021). "Is There an App for That?: Ethical Issues in the Digital Mental Health Response to COVID-19." AJOB Neurosci: 1-14.	Well before COVID-19, there was growing excitement about the potential of various digital technologies such as tele-health, smartphone apps, or AI chatbots to revolutionize mental healthcare. As the SARS-CoV-2 virus spread across the globe, clinicians warned of the mental	2021	Canada	Psychiatry	Review, narrative	Discussing the opportunities for AI in psychiary and the risk of inequalites. Potential benefits low, risk of inequality high!	Many digital and AI tools suggested as part of C19 recovery in mental health are likely inefficient. Resources should instead be put on fixing existing inequalities with evidence-based methods. Only 2 of 73 apps on Google Play had evidence of efficacy.	1. Digital divide. 2. Increased availability. 9. Skewed datasets	Investment and adaptation of new technologies will be biggest in high SES. Also risks pushing SDH interventions aside.					
Obermeyer, Z., et al. (2019). "Dissecting racial bias in an algorithm used to manage the health of populations." Science 366(6464): 447-453.		2019	USA	General Healthcare	Quantitative	Comparison of biomarkers for mobidity (HBA1C and creatinin) and recommendations by an AI to offer them extra care on their health insurance, by race.	Black americans needed to be significantly more ill to be recommended, "problem formulation" of using costs as a proxy for need, in a society where Black communities spend less money on care for all kinds of reasons (access, cost etc).	10, 11.			The importance of involving target communities along the whole development process to avid faulty problem formulations.			
Razzaki, S., et al. (2018). "A comparative study of artificial intelligence and human doctors for the purpose of triage and diagnosis." arXiv preprint arXiv:1806.10698.		2018	UK	Primary care	Quantitative	Comparison of Babylon Triage with four GPs for triaging patients to A&E, GP, nurse, home.	Babylon slightly surpasses GPs "safety" (i.e. sensitivity) and slightly underperforms in "appropriateness" (specificity), is around 90/80 percent correct respectively. Notably no mention of equality or risk of bias.							
Romero-Brufau, S., et al. (2020). "A lesson in implementation: A pre-post study of providers' experience with artificial intelligence-based clinical decision support." Int J Med Inform 137: 104072.	BACKGROUND: To explore attitudes about artificial intelligence (AI) among staff who utilized AI-based clinical decision support (CDS). METHODS: A survey was designed to assess staff attitudes about AI-based CDS tools. The survey was anonymously and voluntarily	2020	USA	Primary care	Qualitative	Qual study of primary care staff before and after an AI decision support tool for diabetes management. Focus on implementation. Survery before and after for different parts of the consultation.	Users were not satisfied. Reasosns included that clinicians wanted to see why something was recommended; explainable, otherwise not trustworthy.	5. (sort of): AI not able to work with SDH and psych as not as quantifiable.		AI in this form porly suited to work with SDH and individual factors such as unemployment etc.	Poor acceptance as doctors found it obvious that it did not take SDH into account. Need to be clear what the AI can and cannot do, so it can complement doctors instead of replacing/replicating.			
(2018). Artificial Intelligence in Healthcare, Academy of Royal Medical Colleges.	The contents represent a series of one-to-one interviews conducted over the spring and summer of 2018 and two focus groups held in July 2018. Most quotes are attributed where practical while some other views have been aggregated to provide a more general view. Dr Farzana Rahman	2018	UK	General Healthcare	Report	Commisioned by NHS Digital, report on various aspects of AI in healthcare. Very comprehensive.	Holistic and human care hard to replicate, health promotion may suffer. Discusses bias. Also: Is it publically acceptable to stratify patients by ethnicity, postcode, socioeconomy etc, if it may improve healthcare? AI could enable doctors to be more human and do more of what they	1, 2, 5: lonelyness and social needs unlikely to be dealt with well by AI (but are they dealt with all that will right now?) 9, 10, 11	Risk that the healthcare system becomes overwhelemed by the "worried well" due to these using AI systems excessively and interpreting it wrongly (e.g. Babylon)	Some degree of dehumanisation likely long-term. Would the role of the doctor as trustworthy and "unique" change if everyone can have an AI in their pocket? Who would they trust the most?	Risk that the healthcare system becomes overwhelemed by the "worried well" due to these using AI systems excessively and interpreting it wrongly (e.g. Babylon). A risk that AI is used where the actual health gains are the least, e.g. Babylon etc. A risk of undermining			
Fiske, A., et al. (2019). "Your robot therapist will see you now: Ethical implications of embodied artificial intelligence in psychiatry, psychology, and psychotherapy." Journal of Medical Internet Research 21(5).	BACKGROUND: Research in embodied artificial intelligence (AI) has increasing clinical relevance for therapeutic applications in mental health services. With innovations ranging from 'virtual psychotherapists' to social robots in dementia care and autism disorder, to robots for	2019	Canada	Psychiatry	Review, narrative	Impacts of AI on psychiatry, short to long term.	AI should not be used to replace human care, but to complement. AI needs transparence and doctors to be aware of biases.	1, 2: Digital divide but more available care. 5. Dehumanisation possible. Likely to strike low SES harder. 6. Dehumanisation may be beneficial in case of stigma.	Risk of using AI as an excuse to reduce care provision (why?). Long-term risk of general societal dehumanisation and worsened inequalities/less empathy.		What happens if an AI detects self-harm when there is noone overseeing it? Is that still better than not having a doctor? And again, risk of using AI to replace real services in rural/underserved communities, worsening care.			
Powell, J. (2019). "Trust Me, I'm a Chatbot: How Artificial Intelligence in Health Care Fails the Turing Test." J Med Internet Res 21(10): e16222.	Over the next decade, one issue which will dominate socotechnical studies in health informatics is the extent to which the promise of artificial intelligence in health care will be realized, along with the social and ethical issues which accompany it. A useful thought experiment is	2019	UK	General healthcare	Discussion	Chatbots cant and shouldnt pass the Turing test: They need to complement rather than replace doctors.	Identifying the complementary positioning of AI tools in health care in general, and in particular for their use in the medical consultation, is a key challenge for the future. We need to understand how to integrate the precision and power of AI tools and practices with the wisdom			The patient-doctor relationship and the human contact is central in healthcare, and AI needs to complement rather than replace, otherwise "wisdom" will be lost. (similar to "metis")				
Joshi, I. and J. Morley (2019). Artificial Intelligence: How to get it right. Putting policy into practice for safe data-driven innovation in health and care. NHSX.		2019	UK	General healthcare	Report	Summary of current (2019) state of AI in healthcare. **Good numbers on active companies and products in the pipeline**. Focus on regulatory frameworks.	Numerous points, mainly on how regulatory frameworks can foster more AI tech in healthcare. Some points about implementation (see to the right).	9,10,11 Bias briefly mentioned.			Build "sandboxes" and pilot schemes to evaluate AI systems, including for "biases". No details. Model impact on the whole clinical workflow.			

Matheny, M., et al. (2019). "Artificial intelligence in health care: the hope, the hype, the promise, the peril." NAM Special Publication. Washington, DC: National Academy of Medicine: 154.		2019	USA	General healthcare	Report	National academy of medicine report outlining successful implementation of AI in medicine.	Augmentation rather than replacement. Clear use case for AI imperative for each application. Consumer-facing health technologies have often worsened inequalites.	9, 10, 11.	Consumer-facing heath-care services tends to widen inequalities?		Equity and SDH needs to be at the centre of implementation and development. Risk of damaging public trust if unequal.			
Ronquillo, C. E., et al. (2021). "Artificial intelligence in nursing: Priorities and opportunities from an international invitational think-tank of the Nursing and Artificial Intelligence Leadership Collaborative." J Adv Nurs 77(9): 3707-3717.	AIM: To develop a consensus paper on the central points of an international invitational think-tank on nursing and artificial intelligence (AI). METHODS: We established the Nursing and Artificial Intelligence Leadership (NAIL) Collaborative, comprising interdisciplinary experts in AI	2021	UK	General healthcare	Qualitative	Summary of discussions at a nursing think-tank on AI and nursing.#	Outlines priorities for how to successfully integrate AI in nursing. 1: Understanding of AI and the impportance of good data, including data collected by nurses. 2. Curriculum needs to be complemeneted by AI teachning. 3. Nurses must be involved in the creation and implementation of				Risk that quantity of care takes over quality of care in nursing if nurses aren't properly involved.			
Organization, W. H. (2021). "Ethics and governance of artificial intelligence for health: WHO guidance."		2021	Switzerland	General Healthcare	Report	Big important piece on successful use of AI in healthcare.	AI will not replace clinicians, but can improve their decisions and provide screening and evaluation tasks in under-resources settings.	1, 2, 3, 5, 9, 10, 11			Risk that AI is seen as panacea for helath problems and diverrts resources away from public health and SDH.			
Whittlestone, J., et al. (2019). Ethical and societal implications of algorithms, data, and artificial intelligence: a roadmap for research. London: Nuffield Foundation.	This report sets out a broad roadmap for work on the ethical and societal implications of algorithms, data and AI (ADA). Their impact on people and society shapes practically every question of public policy, but discussion is not necessarily based on a	2019	UK	General	Report	Directions for research on ethical implications of AI, with recommendations and identified gaps. Comprehensive!	Highlights the incoherence in the use of "bias", "fairness". Also that a biased system may still be more fair than the human decisions it replaces. Simply stating that a system should be fair is not meaningful.	9, 10, 11. Bias and the meaning of bias.			Public involvement key to clarify the concepts and preferences regarding fairness.			
Samorani, M. and L. G. Blount (2020). "Machine Learning and Medical Appointment Scheduling: Creating and Perpetuating Inequalities in Access to Health Care." Am J Public Health 110(4): 440-441.		2020	USA	Primary care	Discussion	Discusses how AI may make access worse for low SES.	AI that books in patients for doctors to see is overbooking more black than white people, as they are statistically more likely to not show up.	10, 11. See original article in references!				1. Samorani M, Harris S, Blount LG, Lu H, Santoro MA. Overbooked and overlooked: machine		
Samorani, M., et al. (2021). "Overbooked and overlooked: machine learning and racial bias in medical appointment scheduling." Manufacturing & Service Operations Management.		2021	USA	Primary care	Quantitative	Demonstrating racial inequality in over-booking systems (Black patients get overbooked more often and thus have to wait longer, as they statistically are more likely not to show up)	Develops a race-aware model, which optimises waiting time first and foremost for the racial group who waits the longest. This removes the racial divide. My own thoughts: Is this fairness? Is this equity rather than equality? It clearly is transformative rather than transparant.	10, 11.						
World Health Organisation (2021). "Global strategy on digital health 2020-2025"		2021	Switzerland	General healthcare	Report	Advise to governments on how to successfully implement digital health solutions, including AI and including ethics.	Importance of wholehearted commitment from governement and need to complement digital health with education, evaluation.	1,2, 9, 10, 11			AI and digital healht will bring big changes and create opportunities to addess SDH - they should be taken. Participatory approaches important in development and implementation. Special care needs to be taken for minorites and populations at risk to be left outside the digital revolution.			
Fukuda-Parr, S. and E. Gibbons (2021). "Emerging Consensus on 'Ethical AI': Human Rights Critique of Stakeholder Guidelines." Global Policy 12(56): 32-44.	Voluntary guidelines on 'ethical practices' have been the response by stakeholders to address the growing concern over harmful social consequences of artificial intelligence and digital technologies. Issued by dozens of actors from industry, government and professional associations, the	2021	UK	General Healthcare	Review, narrative	15 ethical guidelines for AI (in general reviewed)	In terms of equality, strong focus on bias.	10, Bias	Risk of availability bias due to cost. More relevant in private healthcare settings?		Critisising the vagueness of guidelines on implementation, calling for a Human-Rights based approach for equality, participation, accountability.	WHO. (2019) Draft Global Strategy on Digital Health 2020-2024. Geneva: WHO.		
Gottliebsen, K. and G. Petersson (2020). "Limited evidence of benefits of patient operated intelligent primary care triage tools: Findings of a literature review." BMJ Health and Care Informatics 27(1).	INTRODUCTION: There is consistent evidence that the workload in general practices is substantially increasing. The digitalisation of healthcare including the use of artificial intelligence has been suggested as a solution to this problem. We wanted to explore the features of	2020	Sweden	Primary care	Review, narrative	Review of studies on implementation and performance of primary care AI triage systems	Poor evidence base, and generally poor accuracy. Needs better evaluation!				Risk of higher workload and unforseen consequenses from AI triage due to lack of good research.			
Straw, I. (2020). "The automation of bias in medical Artificial Intelligence (AI): Decoding the past to create a better future." Artif Intell Med 110: 101965.	Medicine is at a disciplinary crossroads. With the rapid integration of Artificial Intelligence (AI) into the healthcare field the future care of our patients will depend on the decisions we make now. Demographic healthcare inequalities continue to persist worldwide and the impact of	2020	USA	General healthcare	Discussion	Discussion article looking at the rorigins of inequalities and the role of AI in relation to this.	The shift to AI is a paradigm shift that givens opportunity to address healthcare inequalites, if done right. "we do not have datasets that truly reflect rates of disease, instead we have datasets that are representative of diagnoses and the two do not always align". "We must first question the 'reality of	9, 10, 11. Focuses on algorithmic bias.				ACM Policy Council. Statement on algorithmic transparency and accountability . 2017. https://www.		
Marcus, J. L., et al. (2020). "Artificial Intelligence and Machine Learning for HIV Prevention: Emerging Approaches to Ending the Epidemic." Curr HIV/AIDS Rep 17(3): 171-179.	PURPOSE OF REVIEW: We review applications of artificial intelligence (AI), including machine learning (ML), in the field of HIV prevention. RECENT FINDINGS: ML approaches have been used to identify potential candidates for preexposure prophylaxis (PrEP) in healthcare	2020	USA	General Healthcare, HIV	Review, narrative	Discusses PrEP in HIV and AI to select patients.	From an equality point-of-view: AI was in one study found to identify a large proportion of black patients as high-risk for HIV (28 %), whilst only 4 % of PrEP-users were black. This could either be due to prev underestimation, discrimination or overestimation by the AI.	3, distrust among minorities over security (MSM) 6. (sort of), being able to detect patients who would not otherwise come. 9, 10, 11 (same; patients who were prev missed)			Given the improtance of trust, participatory approaches to implementations is important.			
Straw, I. and C. Callison-Burch (2020). "Artificial Intelligence in mental health and the biases of language based models." PLoS One 15(12): e0240376.	BACKGROUND: The rapid integration of Artificial Intelligence (AI) into the healthcare field has occurred with little communication between computer scientists and doctors. The impact of AI on health outcomes and inequalities calls for health professionals and data	2020	USA	Psychiatry	Quantitative	Using natural langage processing (NLP), they looked at correlation between words as Man, Woman, Black, White with mental health illnesses: "British is to depression what Irish is to alcoholism". They also did a lit rev, and found that onyl a minority of studies of AI using NLP for prediciton had done	Need to do these analysis and assess if the results are corrent or a consequence of sociatal of data-based bias.	10, 11: biases and how to visualise them.						
The Lancet Digital, H. (2019). "There is no such thing as race in health-care algorithms." The Lancet Digital Health 1(8): e375.		2019	UK	General healthcare	Discussion/comment	Importance of system-wide perspective of inequalties.	Refers to Obermeyer reg underlying biases	9,10 , 11	"need to consider the effect on groups and systems" in a wider cultural context. No further info.					
Straw, I. (2021). "Ethical implications of emotion mining in medicine." Health Policy and Technology 10(1): 191-195.	Background: The tools of emotion mining were developed in the field of computer science to detect and evaluate human emotions. The development of social media and digital phenotyping has empowered researchers to apply these techniques to the field of medicine. In recent years we have	2021	USA	Psychiatry	Review, narrative	Specifically discusses emotion mining or sentiment analysis using AI e.g. extracting emotion values from big data on patients (both physiological, social, movement etc).	Focuses on algorithmic bias and the importance of looking at false postives/negatives (specificity and sensitivity) by ethnic and social group. Important to "Mainstream" an understanding of algoritmic bias and fairness in stakeholders (but does not define beyond the above accuracy).	9, 10, 11. Focuses on algorithmic bias.			Emphaisises importance of educating operators/clinical stakeholers throughout the chain in fairness and algorithmic bias (although does not specify).			
Zidaru, T., et al. (2021). "Ensuring patient and public involvement in the transition to AI-assisted mental health care: A systematic scoping review and agenda for design justice." Health Expect 24(4): 1072-1124.	BACKGROUND: Machine-learning algorithms and big data analytics, popularly known as 'artificial intelligence' (AI), are being developed and taken up globally. Patient and public involvement (PPI) in the transition to AI-assisted health care is essential for design justice based on diverse	2021	UK	Psychiatry	Review, narrative	PPI in AI research for mental health, a review of methods and issues to be resolved.	Highlights the need of various forms of PPI to ensure inclusion of population bias, social issus and acceptability in the AI systems.	1, 2, 3 9, 10.	Need to anchor AI in wider cultural settings for acceptability. Related to theme 3.		Focus on PPI as a way of counteracting the power imbalance in designing and implementing mental-health AI.			
Trocin, C., et al. (2021). "Responsible AI for Digital Health: a Synthesis and a Research Agenda." Information Systems Frontiers.	Responsible AI is concerned with the design, implementation and use of ethical, transparent, and accountable AI technology in order to reduce biases, promote fairness, equality, and to help facilitate interpretability and explainability of outcomes, which are particularly pertinent in a	2021	Norway	General healthcare	Review, narrative and quantitative	Looking at research in ethical AI, and clustering studies by themes statistically. Interesting methodology, if not directly applicatbly to my review!	Under "unfair outcomes", focus was on bias and the review highlighted a need to develop methods to measure and mitigate fairness.	9, 10, 11.						

Pham, Q., et al. (2021). "The need for ethnoracial equity in artificial intelligence for diabetes management: Review and recommendations." Journal of Medical Internet Research 23(2).	There is clear evidence to suggest that diabetes does not affect all populations equally. Among adults living with diabetes, those from ethnoracial minority communities-foreign-born, immigrant, refugee, and culturally marginalized-are at increased risk of poor health outcomes. Artificial	2021	Canada	Diabetes	Review,quantitative	118 studies of which 10 reported ethinicity. 10 studies on diabetes managmenent-AI, analysis of share of various ethinicties in training data.	Ethnicity rarerly reported. When reported, majority white (but smaller share than population in Canada) and no on indiginous people. Gives adivise on checking a AIs: 1: does the underlying information describe varaitions in prevanlence by ethnicity, 2 + 4: Does the research describe	9. Underrepresentation in diabetes studies/AI. Sometimes poor ways of correcting bias. http://paperpile.com/b/Mk3QOF/QN3U						
Khan, S. M., et al. (2021). "A global review of publicly available datasets for ophthalmological imaging: barriers to access, usability, and generalisability." Lancet Digit Health 3(1): e51-e66.	Health data that are publicly available are valuable resources for digital health research. Several public datasets containing ophthalmological imaging have been frequently used in machine learning research; however, the total number of datasets containing ophthalmological	2021	UK	Ophtalmology	Systematic review, quantitative	Oversight of all publically available retinal-photo databases, which is what is used to train AIs.	Poor reporting on ethicity, age, gender in most databases, creating likley bias-problems. Also other issues with underrepresantation of some illnesses and poor accessability to databases.	9						
Liaw, W. and I. A. Kakadiaris (2020). "Primary Care Artificial Intelligence: A Branch Hiding in Plain Sight." Ann Fam Med 18(3): 194-195.		2020	USA	Primary care	Discussion		The 7th challenge is the missing ability of AI to create a bond with the patient.	3. Distrust. 6. AI cannot connect emotionally with patients.						Yes
Howard, A. and J. Borenstein (2018). "The Ugly Truth About Ourselves and Our Robot Creations: The Problem of Bias and Social Inequity." Sci Eng Ethics 24(5): 1521-1536.	Recently, there has been an upsurge of attention focused on bias and its impact on specialized artificial intelligence (AI) applications. Allegations of racism and sexism have permeated the conversation as stories surface about search engines delivering job postings for well-paying technical jobs to men and not	2018	USA	General society	Dicussion		The difficulty of reducing biases.	3. Distrust 10.Underlying bias.11.mitigate previous bias	No		Strong emphasis on the importance of community- and stakeholder consultations before implementing any AI (incl medicine)			Yes
Ursin, F., et al. (2021). "Diagnosing Diabetic Retinopathy With Artificial Intelligence: What Information Should Be Included to Ensure Ethical Informed Consent?" Front Med (Lausanne) 8: 695217.	Purpose: The method of diagnosing diabetic retinopathy (DR) through artificial intelligence (AI)-based systems has been commercially available since 2018. This introduces new ethical challenges with regard to obtaining informed consent from patients. The purpose of this work	2021	USA	Ophtalmology, Primary care	Review, qualititative	Discusses both ethical and practical issues with ophtalmology AI in primary care.		2, 9. No elaboration		Importance of addressing patients uncertainty/overconfidence (ICE) in AI, which also calls for GPs to be informed about pros and cons, incl bias.				Yes
Vayena, E., et al. (2018). "Machine learning in medicine: Addressing ethical challenges." PLoS Med 15(11): e1002689.	Effy Vayena and colleagues argue that machine learning in medicine must offer data protection, algorithmic transparency, and accountability to earn the trust of patients and clinicians.	2018	Switzerland	General Healthcare	Discussion	Main ethical issues, short discussion piece.		9, 10			Need for strong routines in both assessing datasets and indentifying bias after AI has been created.			Yes
Williams, C. (2020). "A Health Rights Impact Assessment Guide for Artificial Intelligence Projects." Health Hum Rights 22(2): 55-62.	Artificial intelligence (AI) is being hailed by various actors, including United Nations agencies, as having the potential to alleviate poverty, reduce inequalities, and help attain the Sustainable Development Goals (SDGs).1 Many AI projects are promoted as making important contributions to	2020	UK	General Healthcare	Framework	This perspective argues that the way to mitigate these risks is to conduct a health rights impact assessment prior to their implementation. It introduces a tool that enables a systematic process of health rights assessment to take place.			Risk of too uncareful implementation, myopic focus on a single problem and causing system effects such as "a new project attracting all the healthcare workers" or "overloading diagnostic services".		Presents a framework (or questionnaire) based on the principles of Right To Health, and puts a focus on system factors such as sustainability, staff distribution, integration in the current HC system.			Yes

Annex 4: GRIPP2 Short Form of public involvement

Adapted from Staniszewska et al (1).

Section and topic:	Item:	Reported in section:
1: Aim	Report the aim of PPI in the study	Methods: Public Involvement
2: Methods	Provide a clear description of the methods used for PPI in the study	Methods: Public Involvement
3: Study results	Outcomes—Report the results of PPI in the study, including both positive and negative outcomes	Results: Selection of Publications
4: Discussion and conclusions	Outcomes—Comment on the extent to which PPI influenced the study overall. Describe positive and negative effects	Discussion
5: Reflections/critical perspective	Comment critically on the study, reflecting on the things that went well and those that did not, so others can learn from this experience	Discussion

1. Staniszewska S, Brett J, Simera I, Seers K, Mockford C, Goodlad S, et al. GRIPP2 reporting checklists: tools to improve reporting of patient and public involvement in research. bmj. 2017;358.