AI Interventions in Cancer Screening: Balancing Equity and Cost-Effectiveness

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Abstract

This paper examines the integration of artificial intelligence (AI) into cancer screening programmes, focusing on the associated equity challenges and resource allocation implications. While AI technologies promise significant benefits—such as improved diagnostic accuracy, shorter waiting times, reduced reliance on radiographers, and overall productivity gains and cost-effectiveness—current interventions disproportionately favour those already engaged in screening. This neglect of non-attenders, who face the worst cancer outcomes, exacerbates existing health disparities and undermines the core objectives of screening programmes.

Using breast cancer screening as a case study, we argue that AI interventions must not only improve health outcomes and demonstrate cost-effectiveness but also address inequities by prioritising non-attenders. To this end, we advocate for the design and implementation of cost-saving AI interventions. Such interventions could enable reinvestment into strategies specifically aimed at increasing engagement among non-attenders, thereby reducing disparities in cancer outcomes. Decision modelling is presented as a practical method to identify and evaluate these cost saving interventions. Furthermore, the paper calls for greater transparency in decision-making, urging policymakers to explicitly account for the equity implications and opportunity costs associated with AI investments. Only then will they be able to balance the promise of technological innovation with the ethical imperative to improve health outcomes for all, particularly underserved populations. Methods such as distributional cost-effectiveness analysis are recommended to quantify and address disparities, ensuring more equitable healthcare delivery.

Introduction

The UK National Health Service (NHS) faces significant challenges. Above all, the NHS grapples with long waiting times[1]. NHS England strives to initiate treatment for 85% of cancer patients within 62 days of an urgent referral, but it has fallen short of this target since last achieving it in December 2015. During the first half of 2024, only 65.9% of cancer patients in England received treatment within the target timeframe, resulting in over 30,000 patients experiencing delays. If performance remains consistent this means that by June 2029, an additional 301,000 patients would have faced similar delays[1]. There has also been a fall in the number of patients able to be screened for cancer. This is shown in a decline in attendance across all UK screening programmes following the COVID-19 pandemic and its associated lockdowns, which has remained low[2]. For instance, in breast screening, the pre-pandemic rate was 74.9% (2018), whereas post-pandemic it has fallen to 66.4% (2023)[3]. A plausible explanation for the long waiting times and reduction in screening is that healthcare resources were diverted to address the immediate demands of the pandemic, resulting in a backlog that is currently being managed[2]. In addition, the NHS faces recruitment challenges, and large staff shortages, particularly for key screening staff such as radiographers[4]. These shortages have contributed to delays in 2024 of people with breast cancer receiving a diagnosis and accessing life-changing treatments that could give them the best chance of survival.

It is accepted that AI can play a significant role in addressing these challenges[5-6]. AI-driven technologies tend to be labour-saving, reducing the demand for key screening personnel such as radiographers. This allows the workforce to be reallocated to other areas. Secondly, AI can improve the speed of diagnosis, which directly contributes to shorter waiting times. Thirdly, AI improves the accuracy of screening, enabling earlier detection of conditions when they are more manageable and less costly to treat. For these reasons, AI is a central element of the NHS Long Term Plan[6]. It has already seen significant backing. To tackle delays in cancer diagnosis and treatment, there was a £15.5 million investment from the government in May 2024[7]. The UK's Health and Social Care Secretary announced a target to cut waiting time, highlighting the use of AI to enable 'diagnosis earlier and more accurately and treat more quickly and effectively'[8].

We recognise the benefits of investing in potentially cost-effective AI technologies, but argue it raises important equity concerns. Specifically, current investments in AI disadvantage individuals who do not participate in screening programmes. In the UK, screening programmes are funded through the NHS budget, which includes a key objective of reducing healthcare inequalities, as do all NHS screening programmes. This is outlined in Public Health England's

'Screening inequalities strategy' (2020)[9]. Non-attenders experience the worst cancer outcomes. In the absence of proposals for AI interventions that target screening non-attenders, we argue AI interventions are funded at the expense of critical interventions that benefit non-attenders. This is inefficient, as the health gain from investment is largest when directed at those with the poorest cancer outcomes. Neglecting non-attenders exacerbates poor health outcomes for society's most disadvantaged while deepening existing disparities in cancer outcomes. Therefore, neglecting this group directly contravenes the stated equity objectives of the breast screening programme which is to reduce health disparities.

One solution we propose is that AI interventions should not merely be cost-effective, but ideally cost-saving. In this paper, we provide the rationale for this position, and demonstrate it is practicable solution by explaining how cost-saving AI technologies could be designed and discovered. But if AI interventions are to be implemented without cost savings, we argue that fair treatment for non-attenders requires government policies that promote transparency in investment decisions, particularly in matters related to who bears the brunt of disinvestment.

The argument presented in this paper could potentially apply to the introduction of AI in a variety of screening programmes. However, we focus on AI in breast cancer because the NHS Breast Screening Programme is the largest in the UK, both in terms of population coverage and budget[10]. Furthermore, in this paper, we define AI interventions as technologies designed to enhance diagnostic accuracy, improve risk prediction for earlier cancer detection, and alleviate staffing shortages by partially replacing the role of staff in reading screens. These AI interventions are currently endorsed by the National Screening Committee[11,12] (NSC) and supported by government funding[7,8].

Why AI screening interventions disadvantage non-attenders

AI screening interventions rely on individuals attending screening appointments, as they typically depend on mammogram data for cancer detection and risk assessment[13,14]. Consequently, non-attenders do not benefit from these technologies, and since AI does not target their engagement, they remain a distinct group unable to benefit from future advancements in screening. This is evident in the fact that, to date, all evaluations of AI interventions have been conducted solely within the screened population[12]. There are interventions which target non-attenders; these include outreach programmes focused on education and reducing cancer stigma, as well as initiatives to enhance cancer outcomes through lifestyle changes or preventive medicine. These approaches have been extensively examined, with a recent systematic review of randomized controlled trial evidence on breast screening uptake interventions concluding that all ten interventions reviewed were effective in increasing screening attendance[15]. Yet, they have not been implemented nationally within the NHS. This is reflected in their absence from current screening guidelines[16], as well as in the National Screening Committee's policy proposals, which continue to prioritise AI technologies while neglecting strategies to engage non-attenders. While recognising that AI detection technologies could also benefit non-attenders once they begin attending, the fact remains that underlying barriers continue to prevent their participation in screening.

Data from UK screening programmes underscore the potential for these access barriers to be addressed through targeted investment. Attendance across all UK screening programmes declined following the COVID-19 pandemic because immediate healthcare needs took precedence, leaving screening programmes with backlogs and reduced capacity[2,4]. This scenario highlights the link between investment and attendance: when resources are redirected or insufficient, barriers to participation arise. Given the recent and persistent low rates of attendance[2,3], it is reasonable to conclude that subsequent investments have not focused on non-attenders. Instead, new investments in AI-based interventions have been targeted at attenders. This suggests that post-pandemic screening investments in AI have been chosen over initiatives that could increase attendance to pre-pandemic levels.

Why failing to engage non-attenders in screening programmes is inefficient and inequitable

Failing to engage non-attenders in screening programmes is inefficient and inequitable, and for these reasons, it contravenes the core principles of the NHS as stated in its constitution. It does not use its resources efficiently to deliver the best possible health outcomes for the population. This is because non-attenders have the poorest health outcomes and therefore stand to gain the most from screening[17]. It is inequitable because screening does not serve the entire eligible population, failing to ensure access for all. This failure constitutes an inequity for two reasons. First, lack of access is driven by social disadvantage (referred to in the literature as the social determinants of health)[18] but access is amenable to screening policy interventions[15]. Secondly, lack of access results in poor health outcomes for these socially disadvantaged non-attenders[19], amplifying the harms from social inequity and widening existing health inequalities. We discuss each point in turn.

Effectively using resources to maximise health in the population

Maximising health outcomes from the screening budget requires engaging non-attenders. This is because non-attenders face the poorest health outcomes, as their cancers are often diagnosed at more advanced stages. This results in more difficult and expensive treatments, diminished quality of life, and lower survival rates. The substantial benefits of engaging non-attenders in screening programmes are evident from evaluations of implementation of national breast screening programmes, which demonstrated cost-effectiveness in previously unscreened populations[20] and this finding has been reaffirmed in the UK recently[21]. Expanding screening to current non-attenders is worthwhile because their cancers will be diagnosed early which means saving money from expensive treatments. For example, in 2024 a very large proportion of cancers detected early were through screening, with 84% of non-invasive cancers identified through screening compared to 87% of metastatic cancers diagnosed outside of screening appointments[22]. Engaging non-attenders reduces breast cancer mortality, the most recent estimate is a 38% reduction among women who participate in screenings[19]. Therefore, there is significant potential for cost-effective interventions targeting non-attenders, and candidates could be selected from effective interventions highlighted in a recent systematic review[15]. Additionally, screening attendance serves as a gateway to accessing preventive measures such as lifestyle advice and risk-reducing medications. These are particularly beneficial for non-attenders, who are often socioeconomically deprived and at higher risk of poor cancer outcomes[18,19]. Without targeted efforts to engage this group, they are denied essential preventive care when they are the individuals who need it most[23].

Neglecting equitable access, and widening health inequalities

Failing to engage non-attenders prevents equitable access. A systematic review and meta-analysis of 66 studies on breast cancer screening attendance identified the key barriers to participation to be lower socioeconomic status, lower income, immigrant status, and renting rather than homeownership[18]. In the UK, screening attendance is particularly low among women from the most deprived areas and among ethnic minorities[24]. These findings make it clear that non-attendance is not simply a matter of personal choice but is heavily influenced by societal disadvantages. There are interventions proven to increase attendance[15], which would help address the consequences of these inequitable barriers to access. Therefore, neglecting non-attenders contradicts the principle of providing 'access for all'. This in turn perpetuates and deepens another inequity. Non-attenders already experience poorer health outcomes, likely due to their low socioeconomic status[17,24]. Therefore, neglecting this group exacerbates their already poor health outcomes and widens the health outcome gap between attenders and non-attenders, increasing population-level health inequalities.

We have argued that failing to engage non-attenders is not only an inefficient use of resources but also a fundamental violation of equity and public health objectives. Therefore, it becomes important to rethink how AI interventions are planned, prioritised, and funded to ensure that those least likely to participate in screening are not overlooked or excluded.

Healthcare decision making bodies, such as The National Institute for Health and Care Excellence (NICE), generally operates on the principle of cost-effectiveness; if an intervention is shown to be cost-effective within a specified threshold, it is approved for use in the NHS. The threshold embodies the fundamental economic concept of opportunity cost. Whenever a new intervention is approved, the additional funds required must be found by disinvesting from other interventions that currently help other patients. This assumes a zero-sum approach when deciding whether to invest in a new technology, because any new investment necessarily involves trade-offs even in a situation of an increase in the NHS budget.

We argue that this standard is insufficient under current screening circumstances and introduce a different dimension. New AI-driven cancer interventions should not only deliver additional clinical benefits but be either cost-neutral (incurring no additional costs) or cost-saving (providing a net benefit).

One objection to our position is that achieving cost savings in economic evaluations of screening programmes is challenging, as screening incurs additional costs compared to no screening. These costs arise from factors such as staffing, equipment investments, and training requirements. While we acknowledge that this limits the range of AI interventions that could be considered, we argue that the available AI interventions meeting these criteria are not being identified because policymakers have not taken responsibility for designing them. We now explain how the objective of designing cost-saving AI interventions can be part of the routine planning process for new screening policies in decision modelling analysis.

Discovering cost-saving AI screening interventions

Economic models are routinely used to assess whether introducing new screening programmes into the UK system would improve women's health while also being a justifiable use of the NHS budget. The term "model" has different meanings in different settings but typically when models are used to provide policymakers with a structured way to make decisions based on quantitative estimates, the term "decision model" is used. These models synthesise evidence from multiple sources and establish policy-relevant outcomes in a scenario where no direct evidence exists, based on clearly stated and justified assumptions and choices of evidence. This makes models particularly well-suited for identifying cost-saving AI interventions[14].

First there is strong evidence that AI interventions can be introduced in ways that save resources, although it remains to be confirmed whether these interventions also result in cost savings. For instance, AI has demonstrated effectiveness comparable to radiographers in detecting cancers, potentially enabling AI to take over this role and allowing radiographers to focus on other tasks within the system[12]. However, a formal evaluation is required to determine whether these interventions genuinely result in cost savings. Decision models are commonly used as an initial step in conducting such evaluations. One reason for their use is their ability to predict the likelihood of an intervention's success in scenarios where no additional healthcare resources, beyond the AI intervention, are available. In these capacity decision models[25], one person's use of a resource restricts another's access to it. For example, a patient's visit to a radiographer generates wait times for others needing the same service and this could delay their cancer diagnosis preventing timely treatment[25].

Second, AI screening programmes can be introduced in a variety of ways, with several variables to consider[12]. These include the start and end age for screening, the choice of screening instruments, the location of screening (e.g., dedicated centers, primary care, or hospitals), the frequency of screening, and whether it should be tailored based on risk characteristics—such as selecting which risk factors to include, defining the number of risk groups, and determining the specific screening programs for each group. Decision models can help filter out a wide range of alternatives to identify, from all the different options, which are cost-saving or which combination are cost-saving[21].

Addressing objections to the requirement that AI interventions be cost-saving

We have argued that the design and planning of cost-saving screening interventions can be achieved through decision models. It could be argued that investing in AI technology, even if not cost saving, is justified when resources are redirected from the broader healthcare system. Similarly, it may be claimed that savings generated by AI do not need to be intentionally or fully reinvested to benefit non-attenders. In both cases, the rationale is that the resources used or reallocated are likely to be equally available to both attenders and non-attenders and, therefore, are not specifically detrimental to non-attenders. However, we raise four objections to this position.

First, even if AI technologies are funded through diverting resources from other NHS sectors, non-attenders cannot become attenders without investment in screening interventions to engage them, a process that will not occur with AI interventions, since they target only attenders. Given that resources allocated to non-attenders have declined in recent years, it is unfair to continue to overlook them, and against the objectives of the screening programme which is to improve outcomes for the entire eligible population. Second, over time, the technology will divert resources away from non-attenders within the screening budget. By detecting more cancers or identifying them earlier, AI increases demand for subsequent screenings, as women diagnosed with breast cancer are offered enhanced screening surveillance. In the UK, enhanced surveillance means moving from three-yearly to annual screenings, using up limited resources. This reduces available funds for interventions targeting non-attenders, who can't benefit from enhanced surveillance. Additionally, more screen-detected cancers through enhanced screening of women with a history of breast cancer will prolong waiting times for cancer treatments. As waiting times worsen cancer outcomes, this will disadvantage those currently on the waiting list, including all non-attending women diagnosed with breast cancer. In fact, it disproportionately impacts them, as their need for timely cancer care is more urgent because their cancers are detected at a later stage when treatment is more challenging[19]. Notably, engaging these women would likely reduce cancer treatment waiting times, which is another reason not to neglect them. Currently, late-stage cancers in this group consume considerable resources, including staff time. These resources could be used more effectively if cancers were detected earlier through screening, thereby reducing the demand for cancer treatments. Even if overall waiting times did increase, it is unlikely that these delays would negate the benefits derived from fewer late-stage cancers, caused by earlier cancer detection through increased screening engagement.

Our third objection is that the cost-effectiveness principle applies when policymakers face a new healthcare technology, like AI interventions, and the comparators represent the best alternatives, typically standard care. However, this is not the case in the UK breast screening programme, where there is uncertainty about whether current screening is optimal and debates about redesigning the programme. For example, the UK is the only OECD country offering mammography every three years, while others offer it every two years. There is also significant interest in the UK tailoring breast screening based on risk[21,23]. In this context, AI cannot be considered cost-effective without comparison to other viable uses of the screening budget. It would be a mistake to introduce AI interventions only to later discover that the funds would have been better allocated to alternatives that were viable at the time the decision was made.

Since AI interventions are intended for routine screening and considering the large number of screenings conducted annually, the potential losses from a misguided investment in AI could be significant. It follows that *for now* the cost-effectiveness findings of AI interventions should not be acted upon by decision makers. It is preferable to wait until policymakers and researchers have identified viable alternatives, beyond the current programme, that can serve as a best practice standard of comparison to the AI technology. Viable alternatives can be explored through decision modelling analysis, as described earlier. Given their flexibility to assess different approaches and for the equity considerations we've highlighted earlier, interventions aimed at increasing attendance should also be evaluated within these models as potential alternatives to AI before AI is definitively deemed cost-effective.

Our fourth objection is that funding AI interventions that are merely cost-effective (but are not cost-saving) leads to resource disinvestment elsewhere in the healthcare system to fund the new technologies. Given that non-attenders, who are more likely to have lower socioeconomic status and belong to minority ethnic groups, tend to have higher healthcare needs across the system, they are disproportionately likely to bear the burden of any disinvestment. Traditional cost-effectiveness analyses do not account for these disinvestments. However, this does not imply that the trade-off is equally likely to be beneficial or not. There are reliable ways to determine whether the trade-off to fund the new intervention is truly worthwhile to the non-attenders, which we now turn to.

Achieving equitable access to screening when cost-increasing AI interventions are implemented

We now consider what is equitable action for non-attenders in circumstances where AI interventions are introduced that are not cost-saving. Our recommendations below do not guarantee equitable treatment for non-attenders but quantify their unjust treatment. This brings their circumstances to light, holds policymakers accountable, increasing the likelihood of fair treatment in the future. Additionally, since our proposals aim to quantify the inequity faced by non-attenders, their application would provide evidence that strengthens the case for introducing cost-saving AI interventions.

In cases where decision makers decide to proceed with AI interventions that are not cost-saving, an equitable approach would involve greater transparency about the trade-offs in these decisions before investment. This includes explicitly communicating who benefits, primarily attenders for AI screening interventions, and who loses out, we expect non-attenders, who may face reduced resources for other treatments and services. One way to address this is to frame the impact of AI interventions in terms of health benefits gained versus health benefits foregone. For example, one year of full health gained by patients attending screenings may result in approximately two years of full health lost for other NHS users. These other NHS users will include all non-attenders, some of whom may ultimately develop more severe cancers than attenders due to missed opportunities for screening, and the resulting delayed cancer detection. We hypothesise that explicitly communicating these trade-offs would encourage policymakers to openly consider the opportunity costs of funding AI interventions. This could also shift public discourse, which currently tends to focus on access and anticipated health gains, toward a more balanced understanding that acknowledges the sacrifices borne by non-attenders to achieve these benefits. Additionally, if policymakers choose not to invest in interventions aimed at non-attenders due to budget limitations, this transparency about trade-offs permits necessary debate about that decision. It also promotes the prioritisation and planning of the allocation of future resources, and we have argued deliberate planning is necessary if non-attenders are to receive interventions that help them engage with screening, when that funding becomes available.

A second way to be transparent on who loses out from AI investment is to evaluate its impact on health inequality and on marginalised groups, not just their overall cost-effectiveness. New analytical methods have enabled policymakers to investigate this, using an approach known as Distributional Cost-Effectiveness Analysis (DCEA)[26]. The first application of DCEA demonstrated the impact of equity-related personal conditions, such as socioeconomic deprivation, has on cancer outcomes in the UK bowel cancer screening programme. DCEA showed there were targeted screening options (personalised, GP-signed letters with tailored information) that could improve attendance amongst individuals with social disadvantage, those living in the most income-deprived areas and from an ethnic minority population, leading to improved population health and significantly reduced health inequalities. To our knowledge, a DCEA has not yet been applied in breast screening, but it has shown similar successes of targeted screening within other national screening programmes. Therefore, we support its use in the assessment of breast screening programmes.

The argument presented in this paper concerns AI screening interventions designed to enhance diagnostic accuracy among existing attenders. This is the type of AI that has been developed and is being considered for introduction into the NHS. However, AI has the potential to improve existing engagement strategies, for example AI automated screening appointment reminders and AI assistance with arranging a suitable screening date and location. In cases where AI technologies provide benefits to both attenders and non-attenders, policymakers should conduct a transparent evaluation, applying the health benefits gained versus health benefits foregone framework to quantify the opportunity cost of this investment for non-attenders. This approach ensures that the trade-offs involved in investing in dual-benefit AI interventions are carefully weighed against the potential advantages of interventions specifically designed to engage non-attenders.

Conclusion

We have argued that funding new AI interventions in breast cancer may perpetuate and exacerbate inequities in cancer care. A major issue is that AI interventions are not designed to target non-attenders and consume resources that could benefit underserved groups. Policymakers often prioritise rapid AI adoption due to its effectiveness, neglecting deliberate planning to address subsequent health disparities between attenders and non-attenders. To address this, cost-saving AI interventions should be prioritised, with savings reinvested to support non-attenders. This approach can be readily implemented using decision modelling. Additionally, decision-making should be more transparent, clearly outlining the opportunity costs and equity implications of AI investments.

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