

# Use of AI in Breast Cancer Screening in England Has a Minimal Impact on Greenhouse Gas Emissions and May Increase Diagnostic Accuracy



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## 01 BACKGROUND

- In England, women aged 50–71 are screened for breast cancer every three years.<sup>1</sup>
- Screening mammograms miss approximately 20% of breast cancers.<sup>2</sup>
- Artificial intelligence (AI) tools, such as Mammography Intelligent Assessment, are being trialled to improve early cancer detection.<sup>3</sup>
- According to the National Cancer Institute, screening mammograms miss about 20% of breast cancers. Early research indicates that AI can detect smaller cancers at an earlier stage.<sup>4</sup> Further, as ~80% of biopsies performed on areas of concern are benign, AI may help to reduce the number of unnecessary biopsies.<sup>4</sup>



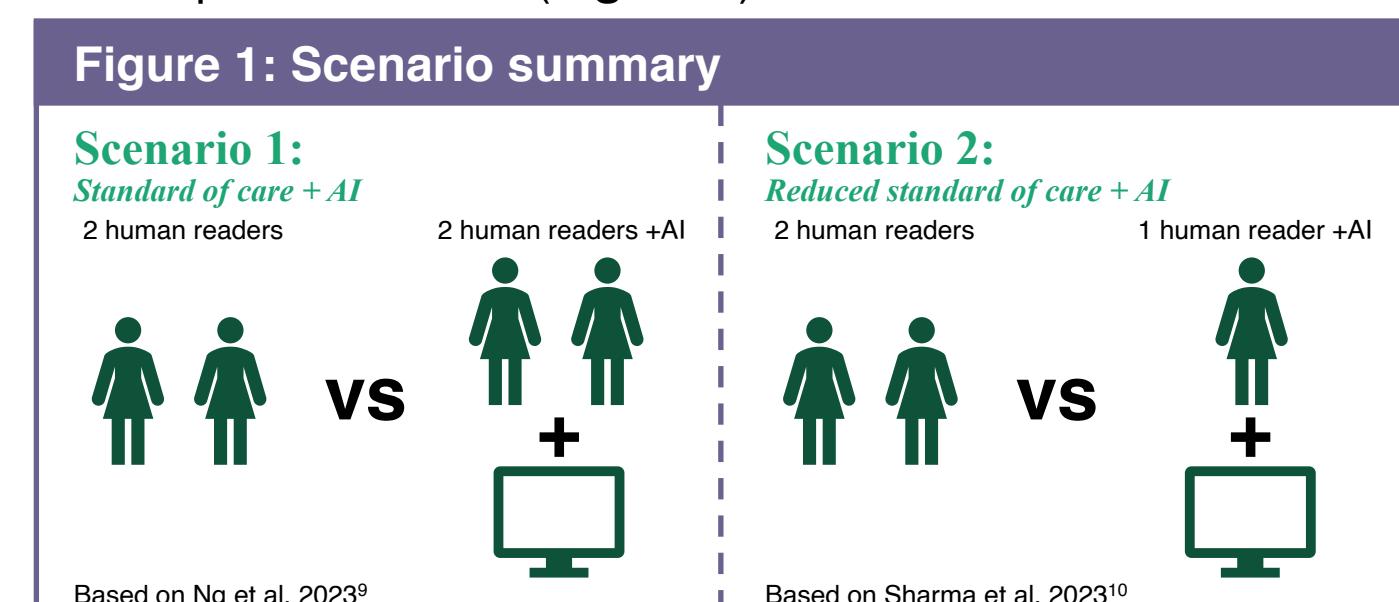
## 02 OBJECTIVE

- The objective of this study was to evaluate the greenhouse gas (GHG) emissions associated with AI-assisted mammography screening versus the current standard of care (SoC), in women aged ≥45 in England over one year (2023–2024).



## 03 METHODS

A life cycle assessment (LCA) was performed using the ReCiPe 2016 v1.1 impact assessment method,<sup>5</sup> with inputs from the ecoinvent database v3.8,<sup>6</sup> and modelled using LCA for Experts (v10.7.1.28).<sup>7</sup> A literature review was conducted to inform the current standard of care pathway.<sup>1</sup> In the SoC pathway, mammogram images were assessed by two human readers, plus a third for arbitration, if required. Real-world baseline data from NHS breast cancer screening statistics in England for 2023–2024<sup>8</sup> were applied to two published scenarios evaluating the use of an AI system as an independent reader (Figure 1).<sup>9,10</sup>



Published values for sensitivity, specificity and arbitration rate<sup>9,10</sup> informed true/false positive and negative values, which determined referrals for triple assessment (clinical examination, imaging, and biopsy) (Table 1).

Table 1. Model parameters for each scenario

| Variable  | Scenario 1 (2 human readers + AI) |           | Scenario 2 (1 human reader + AI) |           |
|---|-----------------------------------|-----------|----------------------------------|-----------|
|   | SoC                               | AI        | SoC                              | AI        |
| Published model variables (%) <sup>9,10</sup>         |                                   |           |                                  |           |
| Sensitivity   | 94.1%                             | 98.8%     | 86.1%                            | 83.9%     |
| Specificity   | 93.7%                             | 93.6%     | 97.1%                            | 97.1%     |
| Arbitration rate                                      | 3.3%                              | 6.2%      | 3.3%                             | 12.3%     |
| Calculated number of patients                         |                                   |           |                                  |           |
| True positive (TP)                                    | 16,677                            | 17,510    | 16,677                           | 16,251    |
| False negative (FN)                                   | 1,046                             | 213       | 2,692                            | 3,118     |
| True negative (TN)                                    | 1,811,784                         | 1,809,850 | 1,875,927                        | 1,875,927 |
| False positive (FP)                                   | 121,817                           | 123,750   | 56,027                           | 56,027    |
| Total screened  | 1,951,323                         | 1,951,323 | 1,951,323                        | 1,951,323 |
| Patients recalled                                     | 138,494                           | 141,260   | 72,704                           | 72,278    |
| Prevalence of cancer in screened population (TP + FN) | 17,723                            | 17,723    | 19,369                           | 19,369    |

A study boundary is shown in Figure 2. Modelled GHG emissions for each module is shown in Table 2.

Figure 2: Scenario summary

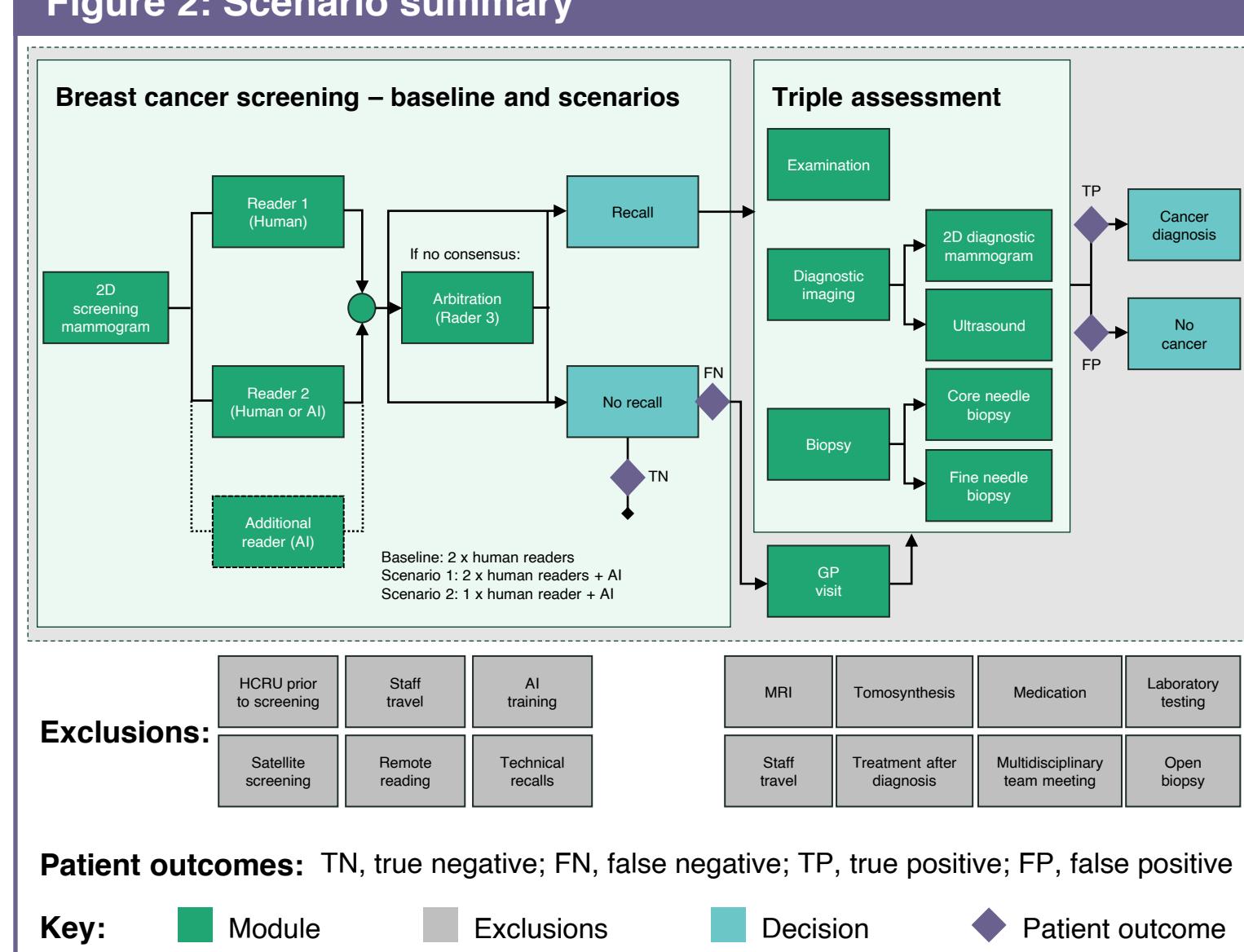
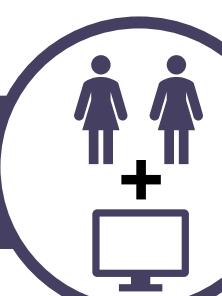


Table 2. GHG emissions associated with the breast cancer screening pathway in England

| Pathway                                   | Module                                  | GHG emissions per module use (kg CO <sub>2</sub> e) |
|---|---|---|
| Screening                                 | Screening return travel                 | 3.812   |
|   | Screening mammogram                     | 0.040   |
|   | Human screen reader                     | 0.001   |
|   | AI screen reader                        | 0.001   |
| Triple Assessment                         | Human screen reader (arbitration)       | 0.003   |
|   | Triple assessment return travel         | 4.273   |
|   | Clinical examination                    | 0.012   |
|   | Diagnostic imaging - mammogram          | 0.049   |
| Triple Assessment Results                 | Diagnostic imaging - ultrasound         | 0.121   |
|   | Core needle biopsy                      | 0.974   |
|   | FNA biopsy                              | 0.716   |
|   | Triple assessment results return travel | 4.273   |
| GP appointment (for false negatives only) | Biopsy results meeting - in person      | 0.022   |
|   | Biopsy results meeting - telehealth     | 0.006   |
|   | GP return travel                        | 3.812   |
|   | GP appointment                          | 0.012   |

AI, artificial intelligence; GP, general practitioner; FNA, fine needle aspiration

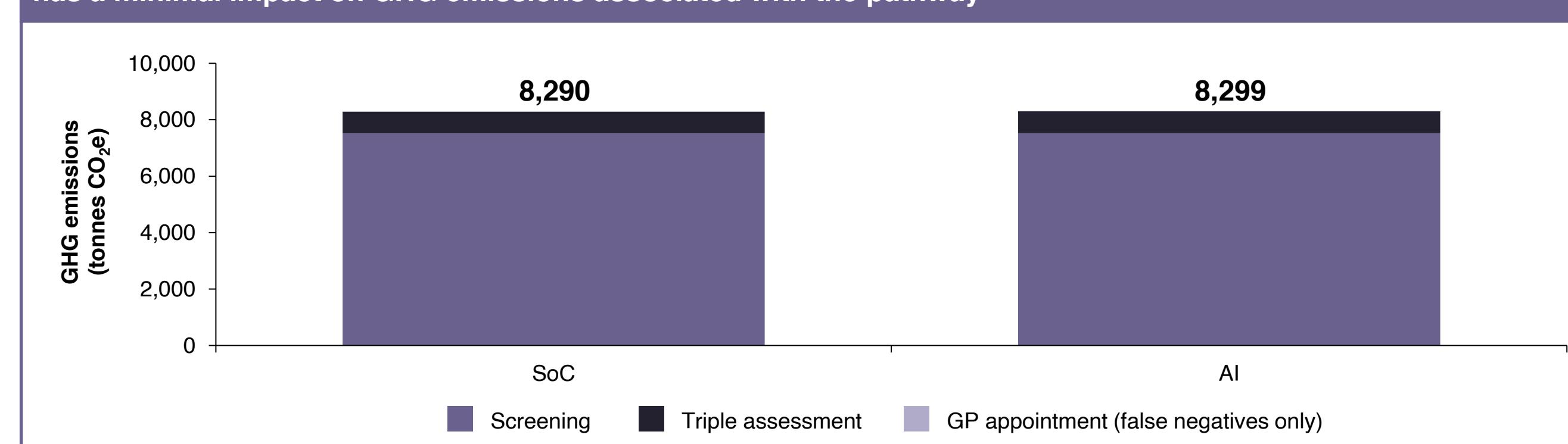
## 04 RESULTS



### Scenario 1: 2 human and 1 AI

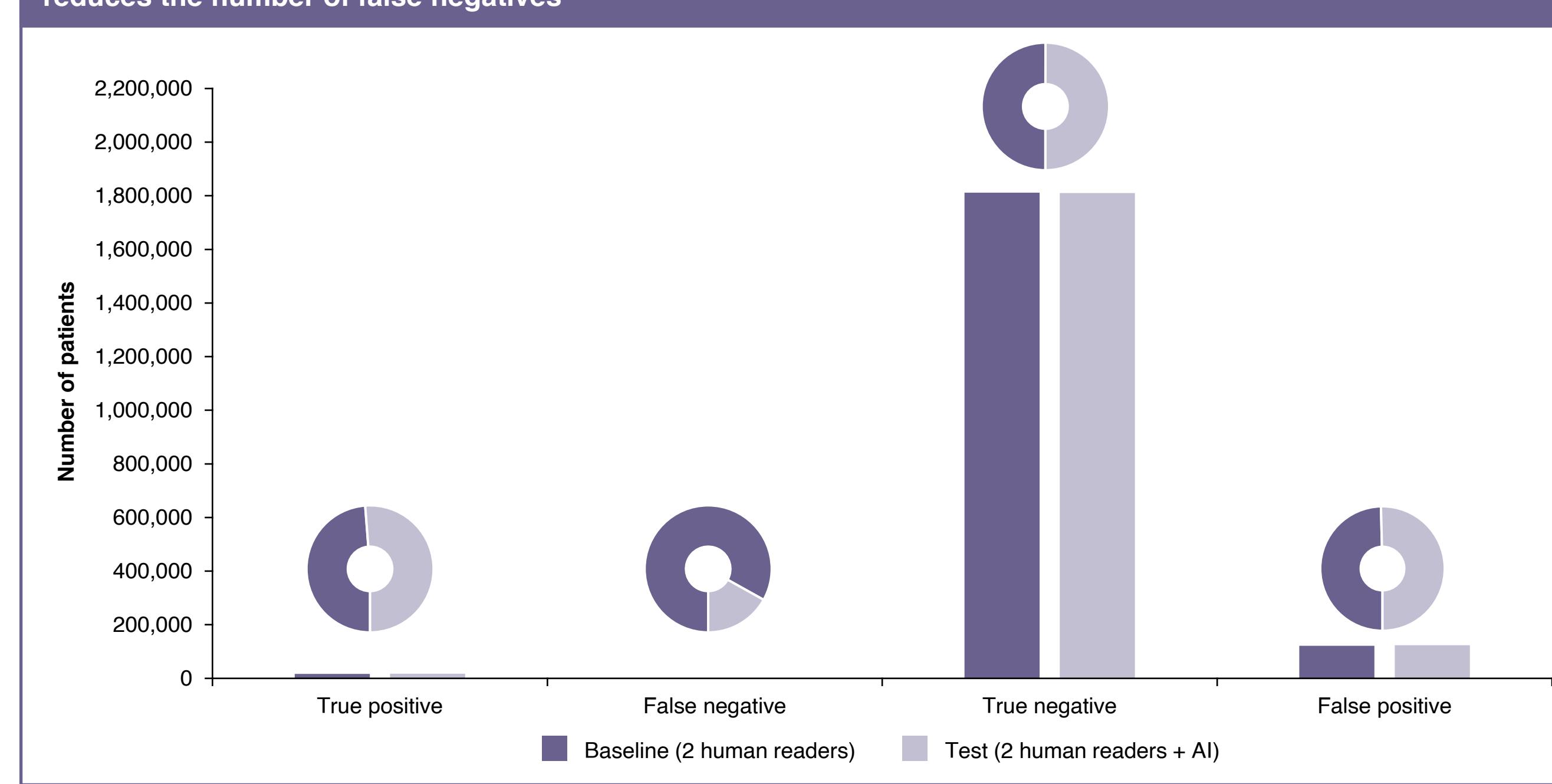
For scenario 1, the SoC pathway generated 8,290 tonnes of carbon dioxide equivalents (CO<sub>2</sub>e). Incorporating an additional AI reader resulted in total emissions of 8,299 tonnes CO<sub>2</sub>e – an annual increase of 9 tonnes, equivalent to the average annual GHG emissions of two people in the UK (Figure 3).<sup>11</sup>

Figure 3: Adding an AI reader alongside two human readers in the breast cancer screening pathway (Scenario 1) has a minimal impact on GHG emissions associated with the pathway



Addition of an AI reader reduces the number of false negatives by 833, decreasing the number of patients incorrectly cleared after screening in the SoC pathway but who subsequently required cancer treatment (Figure 4).

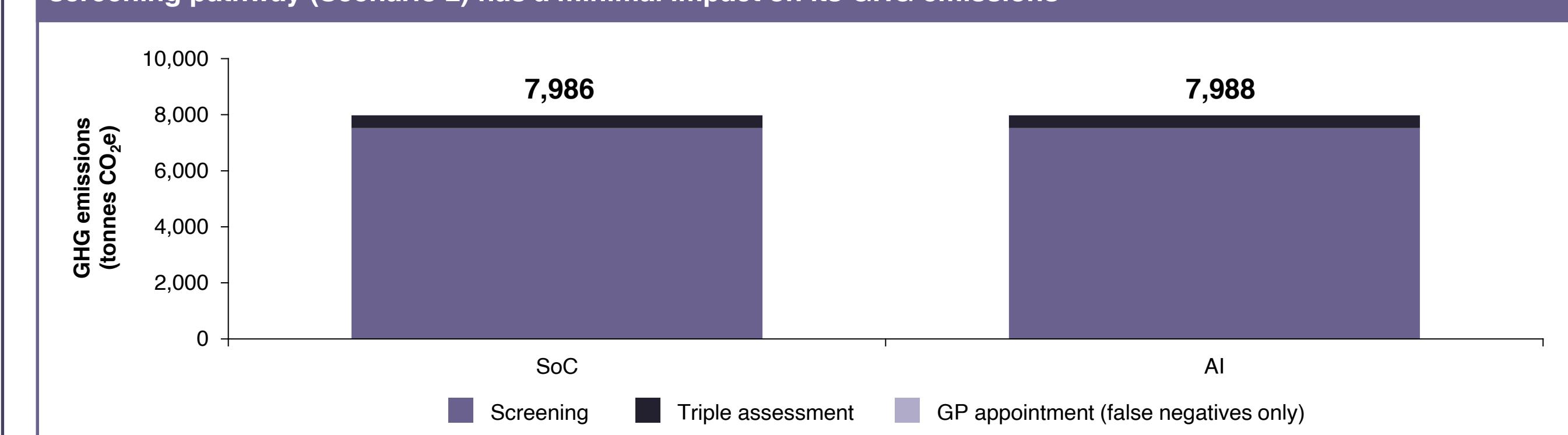
Figure 4: Adding an AI reader alongside two human readers in the breast cancer screening pathway (Scenario 1) reduces the number of false negatives



### Scenario 2: 1 human and 1 AI

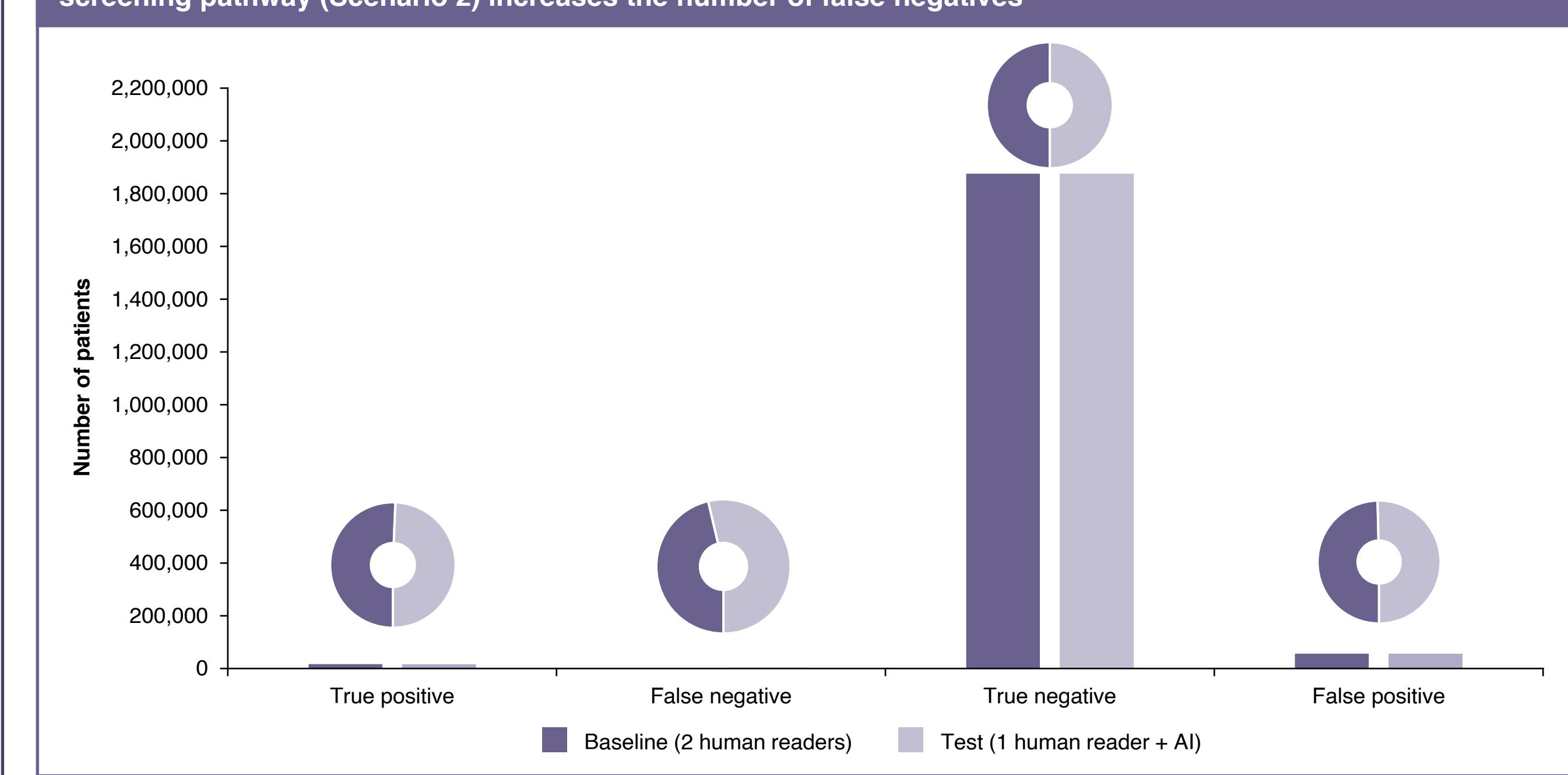
In Scenario 2, replacing one human reader with AI resulted in minimal change, with SoC and the AI-assisted approach generating 7,986 and 7,988 tonnes CO<sub>2</sub>e, respectively (Figure 5).

Figure 5: Adding an AI reader in place of one of the two human readers in the standard of care breast cancer screening pathway (Scenario 2) has a minimal impact on its GHG emissions



Replacing one human reader with an AI reader in the screening pathway leads to 426 patients being incorrectly classified as cancer-free (Figure 6). Clinical outcomes are likely to be worse for these patients, as diagnosis of their cancer will be delayed due to being missed during initial screening.

Figure 6: Adding an AI reader in place of one of the two human readers in the standard of care breast cancer screening pathway (Scenario 2) increases the number of false negatives



## 05 DISCUSSION AND CONCLUSIONS



- Implementing AI assistance in addition to SoC in the breast cancer screening programme in England may result in earlier and more accurate cancer detection, whilst having minimal environmental impact.
- To optimise patient and environmental outcomes, an AI reader should be used as an add-on to current SoC, not replace it.
- When adding AI to current SoC, a minor additional impact is generated by more people being sent incorrectly for further assessment, equivalent to two times the annual GHG emissions of a single person in the UK.
- Future improvements in accuracy of the tool are necessary for implementation of AI in place of a second reader, ensuring patient outcomes remain the primary consideration over environmental benefits.
- While the model focuses on diagnosis, earlier detection could lead to less advanced cancer in some patients, potentially lowering the environmental impact of subsequent treatments.

### References

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