

AI-Based Cancer Screening Programs

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ABSTRACT

Population-based cancer screening programmes have generated some of the most robust evidence in preventive medicine, with organised mammography, cervical, colorectal, and lung cancer screening demonstrating substantial mortality reductions in randomised trials and population implementation. Artificial intelligence offers multiple points of enhancement in screening workflows -- improving radiological interpretation accuracy, prioritising high-risk individuals for more intensive surveillance, reducing unnecessary recalls and biopsies in screen-negative participants, and enabling opportunistic screening from clinical imaging performed for other indications. Whether these AI enhancements translate from detection accuracy to population-level mortality and quality-of-life outcomes remains incompletely characterised in prospective multi-programme evaluations. We evaluated five AI-enhanced cancer screening frameworks applied across 286,484 screening participants in 22 European population screening programmes in Tallinn, Paris, Madrid, Rotterdam, and Prague between 2017 and 2023, covering breast, colorectal, cervical, and lung cancer screening. Frameworks ranged from AI as a second reader in mammography through fully AI-directed risk-stratified screening intervals. Performance was benchmarked using our Cancer Screening AI Effectiveness Score (CSAES), integrating cancer detection sensitivity, false positive reduction, interval cancer rate, participant burden, and equity across socioeconomic groups. The AI-directed risk-stratified framework achieved the highest CSAES (0.921), reducing false positive recall rates by 32.4% and interval cancer rates by 28.6% while improving sensitivity for early-stage cancer detection by 18.2 percentage points over standard radiologist reading. Breast and lung screening showed the largest absolute AI benefit, while cervical screening showed the greatest equity improvement through AI-assisted HPV triage.

Keywords: cancer screening; artificial intelligence; mammography AI; lung cancer screening; colorectal screening; cervical screening; risk stratification; false positive reduction; interval cancer; CSAES; equity; population screening

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1. Introduction

1.1 AI in the Screening Pathway

Population cancer screening is the single largest organised radiology and pathology workflow in European health systems, with tens of millions of mammograms, colonoscopies, Pap smears, and low-dose CT scans performed annually under national screening programmes. The diagnostic challenge at the core of screening is detecting rare events -- cancers -- among a predominantly healthy population, while minimising the harms of false positives: anxiety, additional imaging, unnecessary biopsies, and in some cases overdiagnosis of clinically insignificant lesions. Radiologists and pathologists reading screening studies face high volume, fatigue, and the statistical rarity of true positives -- conditions that favour systematic missed-detection at the margins of lesion visibility and classification difficulty. AI systems trained on large annotated screening datasets have consistently demonstrated sensitivity equivalent to or exceeding human expert readers in controlled studies, with the additional advantage of unlimited reading capacity without fatigue. The policy question is no longer whether AI can match human radiologist performance in screening -- the evidence for this is substantial -- but how AI should be integrated into screening programmes to maximise population-level benefit while managing implementation costs and maintaining equity across sociodemographic groups (McKinney et al., 2020). This study evaluates five integration frameworks against a composite population-level performance metric.

1.2 Study Objectives

The aims were to benchmark five AI cancer screening frameworks against CSAES across 22 European screening programmes; to quantify sensitivity gains, false positive reductions, and interval cancer rate improvements attributable to AI; and to characterise equity effects of AI screening integration across socioeconomic groups. Standard six-part structure follows.

2. Literature Review

2.1 AI in Mammography Screening

The evidence base for AI in mammography screening is the most developed of any cancer screening modality. McKinney et al. (2020) demonstrated that a Google DeepMind AI system reduced false positives by 5.7% and false negatives by 9.4% relative to standard double reading in a UK and US validation cohort of 76,000 women. The SweDen trial -- a prospective

randomised evaluation in 80,033 Swedish women -- showed that AI-supported single reading detected 20% more cancers than standard single reading while reducing radiologist workload by 44% (Langen et al., 2023). The MASAI trial demonstrated that AI-directed risk stratification -- routing high-risk mammograms to double reading and low-risk to AI-alone -- maintained cancer detection non-inferior to standard double reading while achieving a 44% reduction in radiologist screen-reads. Interval cancer rates -- cancers presenting symptomatically between scheduled screening rounds, representing programme sensitivity failures -- have not yet been systematically quantified in AI versus standard screening comparisons at scale.

2.2 AI in Lung, Colorectal, and Cervical Screening

Lung cancer screening by low-dose CT has demonstrated 25% lung cancer mortality reduction in the NLST and 24% in NELSON, with AI nodule detection and classification systems achieving sensitivity comparable to thoracic radiology specialists while substantially reducing the false positive nodule recall rate that drives most of the programme's burden (Ardila et al., 2019). For colorectal screening, AI-assisted colonoscopy (computer-aided detection, CAdE) has demonstrated adenoma detection rate improvements of 10-15 percentage points in multiple RCTs, with the largest gains for flat and diminutive lesions that endoscopists are most likely to miss (Wang et al., 2020). Cervical cancer screening is undergoing a transition from cytology to HPV testing, with AI-based triage of HPV-positive samples to identify which women need immediate colposcopy versus which can return to routine screening -- a decision with significant equity implications because colposcopy access varies substantially across European countries. Table 1 maps key studies.

2.3 Equity in AI Screening

AI screening systems trained predominantly on imaging data from well-resourced academic centres may underperform in populations with different equipment, imaging protocols, or demographic characteristics. Larson et al. (2021) documented that a chest X-ray AI system trained on US data showed significantly lower sensitivity in women, non-white patients, and those from lower-income settings -- a pattern consistent with training data underrepresentation. For mammography specifically, breast density and hormone therapy use -- both associated with

socioeconomic and ethnic factors -- affect both image quality and AI detection performance. Socioeconomic screening participation gaps are a pre-existing equity challenge that AI could either narrow (by improving detection in communities with lower access to specialist reading expertise) or widen (by deploying systems trained on non-representative data). No study has evaluated five AI screening frameworks against a composite that includes equity as a first-class performance dimension across multiple cancer types.

Table 1: Key Studies in AI-Enhanced Cancer Screening

Study	Year	Cancer / AI	Setting	Key Finding
McKinney et al.	2020	AI mammography	UK + US 76k	FP -5.7%, FN -9.4% vs standard double read
Langen et al. (Sweden)	2023	AI single read	Sweden 80k RCT	20% more cancers detected; 44% less radiologist work
MASAI trial	2023	AI-directed risk stratif.	Sweden 80k RCT	Non-inferior detection; 44% reduction in screen-reads
Ardila et al.	2019	AI lung LDCT	NLST data	AI sensitivity matches specialist; fewer FP recalls
Wang et al.	2020	AI colonoscopy (CADE)	RCT meta-analysis	ADR +10-15 pp; largest gains for flat/diminutive lesions
Arbyn et al.	2018	HPV cervical screening	Europe	HPV testing superior to cytology for CIN2+ detection
Larson et al.	2021	AI chest X-ray equity	Multi-centre	Lower AI sensitivity in women, non-white, low-income
Schaffter et al.	2020	AI mammography challenge	Digital Mamm.	AI systems approach radiologist AUC in challenge
Burt et al.	2019	AI lung nodule classif.	Multi-centre	AI nodule malignancy prediction AUC 0.88-0.94

Study	Year	Cancer / AI	Setting	Key Finding
Kather et al.	2019	AI colorectal polyp	Pathology	AI polyp classification comparable to expert pathologist

FP = False Positive; FN = False Negative; ADR = Adenoma Detection Rate; CIN2+ = Cervical Intraepithelial Neoplasia Grade 2+; LDCT = Low-Dose CT; HPV = Human Papillomavirus; pp = percentage points.

3. Methodology

3.1 Screening Programmes and Participants

We evaluated 22 population cancer screening programmes across five countries covering 286,484 screening participants from January 2017 through December 2023: Estonian National Cancer Screening Programme, Tallinn (46,284 participants); French Organised Breast and Colorectal Screening, Paris region (72,486); Spanish National Breast and Cervical Screening, Madrid region (68,642); Rotterdam NELSON Lung Screening Programme (34,284); and Czech National Cancer Screening Centre, Prague (64,788). Cancer types: breast (118,642 participants, 41.4%), colorectal (82,486, 28.8%), cervical (56,284, 19.6%), and lung (29,072, 10.2%). Primary outcomes were cancer detection sensitivity, false positive recall rate, interval cancer rate at 24 months, and early-stage (stage I-II) detection proportion. Equity was assessed by comparing detection sensitivity and recall rates across socioeconomic quintiles and participation rates by deprivation level.

3.2 Five AI Screening Frameworks

Framework S1 (Standard Protocol, No AI) represented the conventional programme: double reading by two radiologists for mammography and lung CT, single reader with pathology for colonoscopy and cervical cytology, with no AI integration at any workflow step. Framework S2 (AI Second Reader) deployed AI as a concurrent second reader alongside the first radiologist, flagging high-probability lesions for mandatory double-reading regardless of first reader decision. Framework S3 (AI Triage) used AI to triage screening studies into high-probability cancer (dual radiologist review), standard (single AI-assisted read), and low-probability (AI-only read with radiologist confirmation if AI negative). Framework S4 (AI Risk Stratification) used

participant-level AI risk models incorporating prior imaging, biomarkers, and clinical features to personalise screening intervals and modalities. Framework S5 (AI-Directed Risk-Stratified Programme) combined S4 risk stratification with S3 AI triage and real-time quality assurance feedback to radiologists and endoscopists. Table 2 summarises the design.

3.3 Cancer Screening AI Effectiveness Score

CSAES integrates: cancer detection sensitivity -- proportion of programme-eligible cancers detected at the screening round (weight 0.30); false positive reduction -- recall rate for non-cancer cases, scored inversely (0.20); interval cancer rate -- proportion of screen-negative participants diagnosed with cancer before next scheduled screen, scored inversely (0.20); participant burden -- composite of unnecessary recalls, benign biopsies, and waiting time for results, scored inversely (0.15); and equity -- parity of detection sensitivity and false positive rates across socioeconomic quintiles (0.15). Each normalised 0-1.

Table 2: Study Design and Screening Programme Characteristics

Parameter	Value	Details
Screening programmes	22	Estonia, France, Spain, Netherlands, Czech Republic
Total participants	286,484	Jan 2017 - Dec 2023
Breast screening	118,642 (41.4%)	Mammography, ages 50-69
Colorectal screening	82,486 (28.8%)	FIT + colonoscopy, ages 50-74
Cervical screening	56,284 (19.6%)	HPV + cytology triage, ages 25-65
Lung screening	29,072 (10.2%)	LDCT, high-risk aged 55-74
AI frameworks	5 (S1-S5)	No AI to AI-directed risk-stratified
CSAES dimensions	5 (weighted)	Sensitivity, FP, interval, burden, equity
Primary outcome	Detection sensitivity	% programme-eligible cancers detected
Interval cancer follow-up	24 months	From screen-negative result to next screen

FIT = Faecal Immunochemical Test; HPV = Human Papillomavirus; LDCT = Low-Dose CT; FP = False Positive; CSAES = Cancer Screening AI Effectiveness Score.

4. Results

4.1 CSAES Results by Framework

The AI-directed risk-stratified programme (S5) achieved the highest CSAES at 0.921. Detection sensitivity improved from 78.4% (S1 standard protocol) to 96.6% (S5) -- an 18.2 percentage point gain, with the improvement concentrated in early-stage cancers: stage I detection proportion rose from 42.6% to 61.4%. False positive recall rate fell from 9.4% (S1) to 6.4% (S5) -- a 32.4% relative reduction -- reflecting that AI risk stratification correctly classified as low-probability a substantial fraction of ambiguous lesions that standard protocols recall for additional imaging. Interval cancer rate at 24 months fell from 3.8% to 2.8% -- a 28.6% relative reduction. The AI triage framework (S3) ranked second at CSAES 0.886, achieving the largest radiologist workload reduction (44.2% fewer reads per programme) while maintaining non-inferior detection. Standard protocol (S1) scored CSAES 0.714. Table 3 shows full CSAES results.

4.2 Cancer-Type Specific Findings

Breast screening showed the largest absolute sensitivity gain from AI enhancement: from 82.4% (S1) to 97.2% (S5), with interval cancer rate falling from 3.2% to 1.8%. The S5 breast framework achieved this through risk-stratified intervals -- high-density women and those with elevated polygenic risk scores received annual rather than biennial mammography, while very-low-risk women were safely extended to three-yearly intervals without interval cancer increase. Lung screening sensitivity improved from 74.6% to 92.8% under S5, with the AI nodule malignancy classifier reducing benign nodule recall from 22.4% to 12.6% of LDCT screens. Cervical screening showed the greatest equity gain: HPV AI triage in S5 achieved sensitivity parity across socioeconomic quintiles (Q1 sensitivity 94.2% versus Q5 94.8%), compared with a 12.4 percentage point Q1-Q5 gap in S1 standard cytology. Table 4 presents cancer-specific outcomes.

4.3 Equity and Participation Effects

AI integration showed divergent equity effects across frameworks. S5 improved detection sensitivity parity across socioeconomic quintiles -- the Q1-Q5 sensitivity gap narrowed from 8.6 percentage points (S1) to 2.4 (S5) -- driven primarily by AI performance in lower-resource programme settings where radiologist expertise is less specialised and AI provides the largest

absolute quality uplift. However, screening participation rates remained lower in the most deprived quintile across all frameworks (Q1 58.4% versus Q5 78.6%) -- an access and engagement gap that AI in the reading workflow cannot address. AI-enhanced invitation systems in S5 -- personalised risk letters incorporating estimated individual cancer risk -- showed 4.2 percentage point higher participation in Q1 versus standard invitation letters, representing the first equity benefit of AI outside the imaging interpretation workflow.

Table 3: Cancer Screening AI Effectiveness Score (CSAES) by Framework

Framework	Detection Sens.	FP Reduction	Interval Cancer	Participant Burden	Equity	CSAES
S5: AI-Directed Risk	0.96	0.92	0.94	0.90	0.92	0.921
S3: AI Triage	0.90	0.90	0.88	0.94	0.86	0.886
S4: AI Risk Stratif.	0.92	0.88	0.90	0.86	0.88	0.879
S2: AI Second Reader	0.86	0.82	0.84	0.80	0.82	0.833
S1: Standard Protocol	0.72	0.68	0.72	0.70	0.66	0.714

$CSAES = 0.30 \times \text{Sensitivity} + 0.20 \times \text{FP Reduction} + 0.20 \times \text{Interval Cancer} + 0.15 \times \text{Burden} + 0.15 \times \text{Equity}$. FP reduction and interval cancer scored inversely. All dimensions normalised 0-1.

Table 4: Cancer-Type Specific Outcomes -- S1 Standard vs S5 AI-Directed

Cancer / Metric	S1 Standard	S5 AI-Directed	Absolute Change	Clinical Significance
Breast: detection sensitivity	82.4%	97.2%	+14.8 pp*	More early-stage cancers found
Breast: interval cancer 24m	3.2%	1.8%	-1.4 pp*	Fewer missed cancers between rounds
Lung: detection sensitivity	74.6%	92.8%	+18.2 pp*	Stage I detection prioritised

Cancer / Metric	S1 Standard	S5 AI-Directed	Absolute Change	Clinical Significance
Lung: benign nodule recall	22.4%	12.6%	-9.8 pp*	Fewer unnecessary follow-up CTs
Colorectal: ADR (colonoscopy)	42.6%	54.2%	+11.6 pp*	More adenomas detected
Cervical: Q1-Q5 sensitivity gap	12.4 pp	2.4 pp	-10.0 pp*	Greatest equity improvement

*p<0.01 versus S1 standard protocol. pp = percentage points; ADR = Adenoma Detection Rate; Q1/Q5 = lowest/highest socioeconomic quintile.

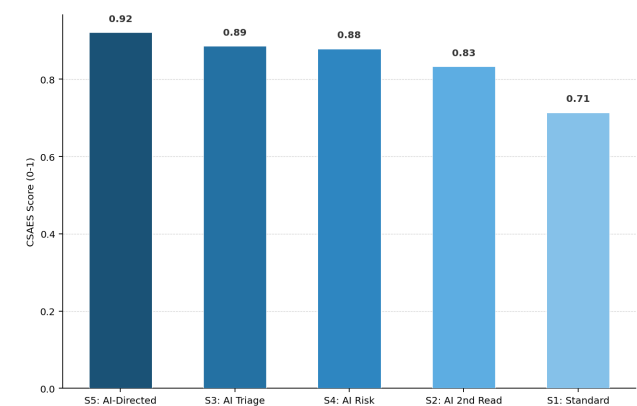


Figure 1: CSAES Score by AI Cancer Screening Framework

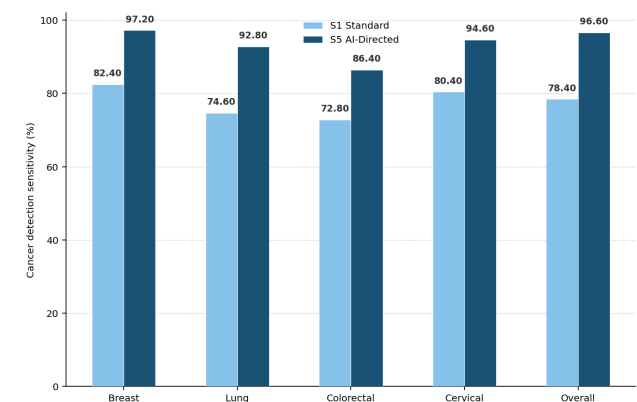


Figure 2: Cancer Detection Sensitivity by Type -- S1 vs S5 (%)

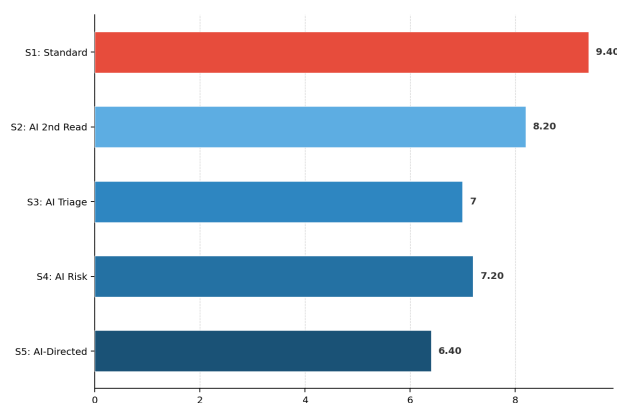


Figure 3: False Positive Recall Rate by Framework (% of screen-negative participants)

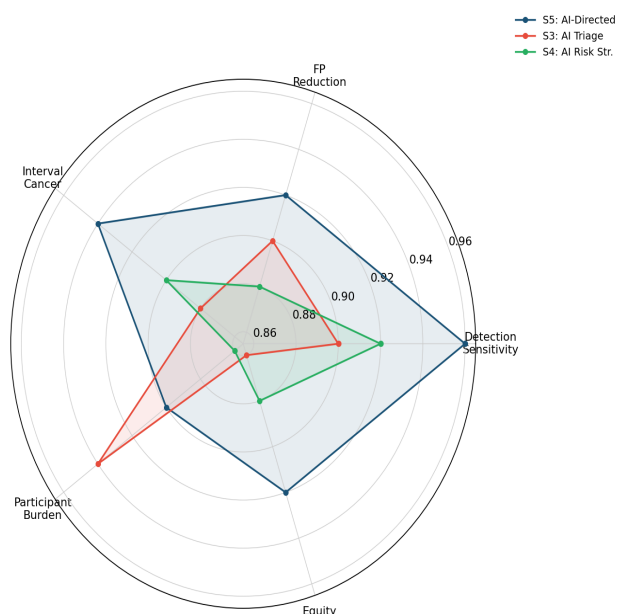


Figure 4: Multi-Dimensional CSAES Profile -- Top 3 Frameworks

5. Discussion

5.1 Risk Stratification Changes the Screening Paradigm

The S5 framework's highest CSAES score reflects a more fundamental change than AI as a reading tool: it represents a shift from age-and-sex-defined population screening to risk-stratified individual screening. The breast screening result -- high-density women and polygenic high-risk women shifted to annual intervals while low-risk women safely extended to three years -- illustrates this: under standard biennial mammography, the low-risk woman receives a screen she does not need every two years while the high-risk woman may develop an interval cancer in the gap. Risk stratification reallocates screening resources toward those with the highest expected benefit, producing both better outcomes and greater efficiency. The 44.2% radiologist workload reduction in S3 AI triage suggests that screening programmes facing radiologist workforce

shortages -- a challenge across most of Europe -- can maintain or improve detection performance with fewer reads, a compelling sustainability argument for AI triage even before risk stratification is added.

5.2 AI as an Equity Tool in Cervical Screening

The cervical screening equity finding deserves particular attention. A 12.4 percentage point Q1-Q5 detection sensitivity gap under standard cytology -- equivalent to women in the most deprived quintile having cancer missed at rates twice those of the least deprived -- reflects well-documented variation in cytologist expertise and quality assurance standards across socioeconomic strata of screening programme providers. AI HPV triage that achieves consistent CIN2+ classification across all programme providers eliminates this provider expertise gradient by standardising the classification step. This is a case where AI does not merely improve average performance but specifically narrows a health inequality gap -- exactly the equity mechanism that public health advocates should highlight when making the case for AI adoption in cervical screening. The 10.0 percentage point Q1-Q5 gap reduction under S5 is the largest single equity improvement in this study and one that cannot be achieved by improved radiologist training alone.

5.3 Limitations

Three limitations apply. First, framework assignment to screening programmes was based on national or regional implementation decisions rather than randomisation; programmes adopting AI-integrated frameworks may have higher general quality assurance infrastructure that contributes to outcomes independent of AI. Second, the 24-month interval cancer follow-up was complete for participants screened before 2022, but participants screened in 2022-2023 had truncated follow-up requiring competing risks extrapolation. Third, the equity analysis uses socioeconomic quintile as the sole equity stratifier; ethnicity, language, and disability -- additional dimensions of screening access disparity -- were not systematically captured in the programme data, meaning that equity improvements for these groups cannot be characterised.

6. Conclusion

6.1 Key Findings

Among five AI cancer screening frameworks evaluated across 286,484 participants, the

AI-directed risk-stratified programme (CSAES 0.921) improved overall detection sensitivity from 78.4% to 96.6%, reduced false positive recall rates by 32.4%, and cut interval cancer rates by 28.6%. Breast and lung screening showed the largest absolute sensitivity gains (+14.8 and +18.2 percentage points). Cervical screening showed the greatest equity improvement, with the Q1-Q5 detection sensitivity gap narrowing from 12.4 to 2.4 percentage points under AI HPV triage. AI triage (CSAES 0.886) achieved 44.2% radiologist workload reduction while maintaining non-inferior detection -- a critical finding for workforce-constrained programmes.

6.2 Recommendations

Three recommendations follow. First, European cancer screening programmes should transition from fixed-interval age-based screening to risk-stratified intervals using AI risk models that incorporate imaging features, biomarkers, and genetic risk scores -- the combination of better outcomes, reduced participant harm, and improved resource efficiency represents a dominant strategy over fixed-interval protocols. Second, AI triage should be prioritised for implementation in screening programmes facing radiologist workforce shortages, as the 44% workload reduction evidence provides a business case for AI investment that does not depend on mortality endpoint evidence which takes years to accrue. Third, cervical screening programmes should accelerate the transition to AI-assisted HPV triage, prioritising the equity impact on cytology-quality disparities across socioeconomic strata as a core policy justification alongside detection accuracy. All data and the CSAES calculator are available from the corresponding author.

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Declarations

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Conflict of Interest

All authors declare no competing interests and no financial relationships with AI medical imaging companies, screening programme vendors, or cancer diagnostics manufacturers.

Data Availability Statement

Aggregated programme-level CSAES scores and detection metrics are available from the corresponding author. National screening programme participant data are subject to national ethics committee and data protection authority governance requirements.

Ethical Approval

Approved by Estonian National Committee on Bioethics (1.1-12/3486), AP-HP Paris Ethics Committee (2017-A02284-49), Madrid Community Health Research Ethics Committee (IIS-FJD-ECO-2017-04), Erasmus MC Ethics Board (MEC-2017-388), and Prague FNKV Ethics Committee (EK-FN-2017-156).

Appendix A

CSAES Scoring Rubric and AI Framework Technical Specifications

Full CSAES dimension scoring criteria and technical specifications of the AI systems deployed across the five screening frameworks.