Healthcare Improvement Scotland | SHTG Advice on health technologies

Innovative Medical Technology Overview| May 2026

Artificial intelligence (AI) estimated computed tomography fractional flow reserve (CT-FFR)

Key messages

- AI-estimated CT-FFR showed good agreement with results from invasive fractional flow reserve (FFR) measurement for assessing functionally significant coronary artery stenosis. The use of non-invasive AI-estimated CT-FFR could avoid the need for invasive FFR in some patients.

- Based on an indirect comparison using invasive FFR as a reference, AI-estimated CT-FFR has similar specificity to conventional non-invasive calculation of CT-FFR using computational fluid dynamics (CFD). This means that the two non-invasive techniques (AI- and CFD-estimated CT-FFR) appear to have a similar ability to rule out clinically important coronary artery stenosis.

- There remains substantial uncertainty about the diagnostic performance of AI-estimated CT-FFR because of variation in the definitions of AI that were used in the literature and how individual studies were conducted.

- No studies have looked at what happens after an AI-estimated CT-FFR test, for example, whether people also had invasive tests, experienced side effects, had better health outcomes or how patients felt about their care. This means that we do not yet know what the overall impact of AI-estimated CT-FFR would be for patients or the health service.

- No studies assessed whether adding CT-FFR to standard CT coronary angiography (CT-CA) provided added value for patient diagnosis compared with CT-CA alone.

- There were no economic studies looking at the costs or cost-effectiveness of using AI-estimated CT-FFR, so we cannot say whether it would offer value for money for the health service.

Definitions

Angina: chest pain that occurs when the blood supply to the heart becomes restricted because the coronary arteries are blocked or narrowed by plaque buildup (atherosclerosis).[1]

Artificial intelligence (AI): an umbrella term for a range of algorithm-based technologies designed to mimic human cognition to solve complex tasks. In healthcare, AI can be used to detect early signs of illness, support diagnosis and assist clinical decision making.[2] Machine learning and deep learning are types of AI.

Area under the curve (AUC): a widely used measure of diagnostic test accuracy. The statistic is bound between 0 and 1, with a value greater than 0.5 generally considered meaningful and a value equal to or greater than 0.8 regarded as indicating good diagnostic performance.[3]

Coronary artery disease (CAD): a common but serious heart condition caused by plaque buildup that narrows or blocks the arteries supplying blood to the heart. CAD is also known as ischaemic heart disease (IHD) or coronary heart disease (CHD).[4]

Coronary artery stenosis: narrowing or blockage of the arteries supplying blood to the heart that is caused by the buildup of plaque along the artery walls.[4]

Deep learning: a type of machine learning that uses artificial neural networks to learn complex patterns from large datasets. These systems can automatically identify important features from raw data without the need for people to manually design them.[5]

Diagnostic odds ratio (DOR): the ratio between the odds of a positive test result in patients with a disease and the odds of a positive test result in patients who do not have the disease. A value of 1 means that a test does not discriminate between patients with and without the disease. Scores greater than 1 indicate discriminatory test ability. A value less than 1 means the test results are potentially misleading. The DOR rises steeply when sensitivity and specificity approach 100%.[6]

Fractional flow reserve (FFR): the ratio between the maximum blood flow through a narrowed coronary artery and the maximum blood flow in a healthy coronary artery.[7]

Invasive coronary angiography (ICA): the gold standard procedure for establishing the nature, anatomy and severity of CAD. A catheter is inserted through a blood vessel in the groin or arm into the heart to identify areas of narrowing or blockage.[8]

Machine learning (ML): a form of AI that uses three main approaches: supervised, unsupervised and reinforcement learning. Supervised learning models are trained on labelled datasets where each input has a known output. The model learns patterns that enable it to make predictions on new data. Unsupervised learning models learn from unlabelled datasets where the AI determines structure by identifying similarities, densities or relationships within the data. Reinforcement learning models interact with an environment through trial and error.

They take actions, receive 'awards' or 'penalties' and refine their strategy to maximise total rewards over time. This approach supports them to learn long-term, goal-directed behaviours.[2]

Negative predictive value: the probability that a person with a negative test result does not have the disease (that is, the number of true negatives as a percentage of total negative results).[9]

Negative likelihood ratio: the probability that a negative test result will occur in a person with the target condition divided by the probability of a negative test result occurring in a person without the disease (that is, 1 – sensitivity divided by specificity).[9]

Percutaneous coronary intervention (PCI): a procedure in which a cardiologist uses a catheter to open narrowed or blocked coronary arteries, often involving balloon angioplasty with or without stent placement.[10]

Plaque (atherosclerotic): a buildup of fats, cholesterol, calcium and inflammatory cells on artery walls. Over time the plaque buildup hardens, resulting in narrowing of the arteries and thickening and stiffening of the artery walls.[11]

Positive likelihood ratio: the probability that a positive test result will occur in a person with the target condition divided by the probability of a positive test result occurring in a person without the disease (that is, the sensitivity divided by 1 – specificity).[9]

Sensitivity: the probability that a person having a disease will be correctly identified by a diagnostic test (that is, the number of true positive results divided by the total number with the disease).[9]

Specificity: the probability that a person not having a disease will be correctly identified by a diagnostic test (that is, the number of true negative results divided by the total number of those without the disease).[9] With CT-FFR calculation, specificity is likely to be a more important diagnostic measure than sensitivity because patients will already have had a CT-CA, which is a highly sensitive test for diagnosing CAD.

The technology and its use

The Scottish Intercollegiate Guidelines Network (SIGN) guideline on stable angina recommends considering computed tomography coronary angiography (CT-CA) for the investigation of chest pain in patients with suspected stable angina where the diagnosis is not clear from their history alone.[12] CT-CA is also recommended by the National Institute for Health and Care Excellence (NICE) as an imaging technique for evaluating coronary artery disease (CAD) in patients with stable chest pain.[13]

CT-CA can exclude the presence of clinically significant obstructive CAD (defined as ≥50% arterial narrowing in the left main coronary artery or ≥70% in the proximal coronary arteries) with a high negative predictive value, especially in low- to intermediate-risk populations.[14] CT-CA has relatively poor specificity for obstructive CAD, which means it can overestimate stenosis severity and cannot determine if the stenosis is causing functional cardiac ischaemia. This can lead to patients undergoing unnecessary invasive coronary angiography (ICA) procedures to assess cardiac ischaemia when they do not have clinically significant disease.[14, 15]

ICA measures FFR invasively using pressure wires placed across the narrowed coronary artery.[13, 14] If blood flow through the artery is normal, the FFR will be 1. FFR values less than 1 indicate reduced blood flow. For example, an FFR value of 0.80, means that the maximum blood flow in the coronary artery being measured is 80% of what it would be if the artery was fully functioning.[7]

CT-FFR uses non-invasive techniques to calculate FFR. CT-FFR combines data from an individual's CT-CA scan with coronary physiology simulations to mathematically model coronary blood flow, pressure and resistance.[13, 14, 16] CT-FFR can measure FRR using computational fluid dynamics (CFD) or artificial intelligence (AI, through machine learning [ML]). CFD-based CT-FFR creates a patient-specific three-dimensional anatomical model of coronary blood flow using data uploaded to supercomputers for analysis using complex mathematical equations.[14, 17] AI-estimated CT-FFR uses AI algorithms to detect anatomical differences in patient CT-CA data to predict coronary artery haemodynamics.[15, 17, 18] Through training, AI-estimated CT-FFR optimises computation performance and significantly reduces processing times compared with CFD-based CT-FFR.[15, 16, 18, 19]

What is innovative about the technology?

AI-estimated CT-FFR is innovative because it provides a non-invasive analysis of FFR using standard CT-CA imaging data without time-consuming, complex CFD computations or invasive FFR measurement.[13, 16, 20] CFD-based CT-FFR can take up to 2 hours to calculate, depending on the complexity of the patient's coronary anatomy and the computer processing speed.[19, 21] In comparison, AI-based CT-FFR can estimate ischaemic risk from coronary artery stenosis within 2 minutes.[15, 22] AI-estimated CT-FFR may reduce the need for ICA in patients with CAD and stable chest pain, helping lower resource use while improving the accuracy of stenosis assessment and strengthening clinical decision making.[20]

Population, setting and intended user

Population

CAD is the leading cause of death in Scotland, with approximately 6,900 deaths each year.[23] CAD rates are, on average, higher in Scotland than the rest of the United Kingdom (UK). As of January 2026, there are approximately 220,000 people living with CAD in Scotland and an ageing, increasing older population may cause these numbers to rise.

One of the current gold standard diagnostic tests for CAD is ICA.[24] Around 250,000 ICA procedures are carried out each year in the UK.[24] There are no specific statistics on the number of ICA procedures conducted in Scotland, but the Scottish Cardiac Audit Programme (SCAP) showed that 9,135 patients in Scotland underwent percutaneous coronary intervention (PCI) for arterial blockages or stenosis in 2024–25.[25] Since PCI procedures typically include ICA as part of the pathway, this provides a reasonable proxy estimate for the annual number of ICAs performed in Scotland.

The intended population for AI-estimated CT-FFR is adults (≥18 years) with stable typical or atypical chest pain with suspected CAD as the cause.[13] Patients with unstable chest pain, known CAD, previous myocardial infarction or previous coronary stenting would not be part of the intended population for AI-estimated CT-FFR.

Setting and intended use

In 2021, Scottish Health Technologies Group (SHTG) recommended that 'Heartflow FFRCT may be considered as an option alongside a set of complementary diagnostic tools for patients with stable, recent onset chest pain symptoms who have undergone CT-CA with adequate image quality.'[26] At the time this recommendation was published, Heartflow estimated CT-FFR using CFD. The manufacturers of Heartflow have since integrated AI into their software to simulate blood flow and calculate CT-FFR values for coronary arteries.[13, 26]

Equality considerations

Geography

Geography can affect health equity and access to healthcare for people living in remote and rural locations. Consequently, the specific needs of remote and rural communities need to be acknowledged and considered when introducing new health technologies.[27] The 2021 SHTG Recommendations on Heartflow noted that 'the use of Heartflow FFRCT should be determined in the context of the diagnostic resources and expertise available to the referring clinician. Heartflow FFRCT may be of particular value in remote locations, when access to complementary diagnostic tools is limited.'[26]

Gender

CAD is often viewed as a disease that only affects men, but women face a disproportionately higher burden of morbidity and mortality associated with CAD and are under-represented in cardiovascular clinical trials.[4, 28] In Scotland, approximately 80,000 women have CAD, one in 12 women will die from the disease and CAD kills more than twice as many women as breast cancer.[23]

CAD, on average, manifests later in life for women compared with men.[28] Women are less likely to recognise the symptoms of heart disease or a heart attack and are more likely to delay seeking help.[29]

In 2024–25 there was a noticeable gender imbalance in PCI procedures for people aged 60–69 years, with 72.9% of procedures in men compared with 27.1% in women.[25] More PCI procedures were performed in women compared with men in older age brackets (75–79, 80–84 and ≥85 years) which may partially reflect the longer life expectancy among women.[25]

Socioeconomic status

The incidence and prevalence of CAD among people living in the most deprived areas of Scotland are 1.8 times higher than among people living in the least deprived areas.[23, 30] Individuals living in the most deprived areas of Scotland are also more likely to die from CAD before the age of 65.[25] In 2024, the age-standardised mortality rate of CAD in the least deprived areas of Scotland was 82 per 100,000 compared with 189 per 100,000 in the most deprived areas.[30] In 2024–25, 21.8% of patients undergoing PCI were living in one of the most deprived areas of Scotland.[25]

AI bias

Bias in AI occurs when the results produced by an AI system are skewed because of human biases in the training data used or in the AI algorithm itself. For example, AI tools could develop bias if the data used to train them does not come from a diverse and representative clinical population. If the AI software is trained on data that mostly includes information about patients from one ethnic group, age bracket, gender, severity of disease, etc, then the AI cannot be guaranteed to work as well for people with different characteristics.[31, 32]

Automation bias may also be introduced by using AI-estimated CT-FFR to diagnose CAD. This refers to bias arising from clinicians' over-reliance on the technology, leading to complacency and reduced human detection of pathology.[33-35]

Summary of clinical and safety evidence

AI-estimated CT-FFR versus invasive FFR (gold standard)

A systematic review with meta-analysis of 17 studies evaluated AI-estimated CT-FFR (ML based) using invasive FFR as the gold standard test.[19] The analysis included 3,255 patients (3,906 vessels) with a mean age of 62 years (standard deviation [SD] 3.7). Studies in the review used three different AI tools: cFFR (versions 1.4 to 3.2), DEEPVESSEL-FFR (versions not specified) and two non-commercial tools.

The authors assessed the quality of the primary studies using the QUADAS-2 (quality assessment of diagnostic accuracy studies version 2) tool.[19] Studies had good applicability and a low risk of bias for the index test domain. More than half the included studies had an unclear risk of bias relating to patient enrolment and three studies had a high risk of bias because of inappropriate exclusion of patients from the study.

The authors concluded that AI-estimated CT-FFR had high sensitivity and specificity and could be considered as a triage tool for non-invasive screening for coronary ischaemia. Per-patient pooled sensitivity and specificity for AI-estimated CT-FFR were 0.86 (95% confidence interval [CI] 0.79 to 0.91) and 0.87 (95% CI 0.76 to 0.94), respectively. The per-vessel analysis reported pooled sensitivity and specificity as 0.80 (95% CI 0.74 to 0.84) and 0.84 (95% CI 0.77 to 0.89), respectively.

Another meta-analysis of 13 studies (n=3,038) evaluated AI-estimated CT-FFR using invasive FFR as the gold standard.[15] No information was provided about the AI tools used to calculate CT-FFR in the included studies and no study participant characteristics were reported.

The quality of the included studies was assessed using the QUADAS-2 tool. Most studies were judged to have a low risk of bias. One study had a high risk of bias relating to the gold standard (invasive FFR) because it did not report the threshold used. More than 25% of the included studies were rated as having an unclear risk of bias because of a lack of information about patient selection.[15]

The pooled sensitivity and specificity for AI-estimated CT-FFR were 0.84 (95% CI 0.79 to 0.87) and 0.83 (95% CI 0.77 to 0.88), respectively. The positive likelihood ratio was 4.95 (95% CI 3.58 to 6.84) and the negative likelihood ratio was 0.20 (95% CI 0.15 to 0.26). This suggests that AI-estimated CT-FFR is 4.95 times more likely to correctly identify CAD than misclassify it and the probability of reporting a false negative was 0.2 times that of true negatives. The diagnostic odds ratio (DOR) was 25.15 (95% CI 14.87 to 42.52) and the area under the curve (AUC) was 0.90 (95% CI 0.87 to 0.93), indicating high diagnostic accuracy. The authors concluded that the diagnostic performance of AI-estimated CT-FFR meant it would be effective at excluding the presence of significant CAD and may therefore reduce the number of patients going on to have unnecessary ICA procedures.[15]

AI-estimated CT-FFR versus CFD-based CT-FFR

A systematic review with meta-analysis of 41 studies indirectly compared AI-estimated CT-FFR with CFD-based CT-FFR, using invasive FFR as the reference test.[18] This indicates that no primary studies have directly compared the diagnostic performance of AI-estimated and CFD-based CT-FFR. In some studies that used CFD-based CT-FFR, ML approaches were used to extract the initial data from CT-CA images before CFD-based calculation of CT-FFR, which blurs the lines between CFD and AI approaches to CT-FFR estimation.

The meta-analysis of AI-estimated CT-FFR included 18 studies (1,323 patients; 4,194 vessels). The mean age of study participants ranged from 57.3 to 70.2 years. The proportion of men in the studies ranged from 58% to 78%. The AI-estimated CT-FFR software used included cFFR, skCT-FFR, XFFR and DEEPVESSEL-FFR.

The meta-analysis of CFD-based CT-FFR included 23 studies (2,501 patients; 3,764 vessels). The mean participant age ranged from 55.2 to 80.0 years. The proportion of men in the studies ranged from 58.0% to 70.8%. The CFD-based CT-FFR tools used included Heartflow, AccuFFRCT, Siemens cFFR, CAscope, COMSOL Multiphysics, uCT-FFR, Autovessel, Coronary Scope, SimVascular, Structural and Fluid Analysis, Beijing Heartcentury and CFX.

The pooled diagnostic performance of CT-FFR calculated using either CFD- or AI-based methods is shown in *Table 1*. The authors concluded that AI-estimated CT-FFR had similar specificity and diagnostic accuracy to CFD-based CT-FFR, but that ML approaches demonstrated lower sensitivity. There was no statistically significant difference between the per-patient specificity of CFD-based CT-FFR and AI-estimated CT-FFR (Z test = -0.59, p=0.55). Pooled sensitivity was statistically significantly higher with CFD-based CT-FFR compared with AI-estimated CT-FFR (Z test = -3.85, p<0.001). There were no statistically significant differences between CFD-based CT-FFR and AI-estimated CT-FFR for per-vessel specificity, DOR or AUC. In the per-vessel analysis, there was a statistically significantly higher sensitivity in the CFD-based CT-FFR group (Z test = -2.05, p=0.04).

Table 1: Diagnostic performance of CFD-based CT-FFR and AI-estimated CT-FFR from two meta-analyses[18]

Analysis	CT-FFR method	Pooled sensitivity (95% CI)	Pooled specificity (95% CI)	Pooled DOR (95% CI)	Pooled AUC (95% CI)
Per-patient	CFD	0.90 (0.87 to 0.92)	0.86 (0.81 to 0.91)	66.66 (39.03 to 113.87)	0.91 (0.87 to 0.93)
	AI	0.83 (0.80 to 0.86)	0.85 (0.80 to 0.88)	31.06 (20.92 to 46.12)	0.87 (0.81 to 0.91)
Per-vessel	CFD	0.87 (0.83 to 0.90)	0.84 (0.79 to 0.88)	38.3 (23.38 to 62.73)	0.91 (0.85 to 0.92)
	AI	0.81 (0.76 to 0.85)	0.87 (0.82 to 0.91)	29.59 (17.58 to 49.80)	0.89 (0.83 to 0.92)

CT-CA with CT-CA plus CT-FFR

No studies were found that directly compared CT-CA with CT-CA plus AI-estimated CT-FFR so any additional benefits of AI-estimated CT-FFR remain unclear.

Evidence limitations

The systematic reviews and meta-analyses above all reported substantial heterogeneity, which may be partly attributable to variation in the FFR thresholds used to define clinically significant stenosis across primary studies. Although AI-estimated CT-FFR can be applied across the full spectrum of coronary stenosis severity, some studies used an FFR cut-off of 0.50, while others used 0.80. In addition, because AI-based CT-FFR estimation relies on high-quality CT images, differences in diagnostic performance may reflect inconsistent handling of low-quality scans. Some studies excluded poor-quality images prior to AI estimation of CT-FFR, thereby inflating accuracy, while others applied the AI algorithm to all images regardless of quality.

The systematic reviews and meta-analyses were also based predominantly on retrospective studies, which are more susceptible to selection bias and incomplete or missing data. One meta-analysis (Lian et al, 2025) noted that compared with prospective studies included in their review, retrospective studies may have overestimated the diagnostic accuracy of AI-estimated CT-FFR.[15] None of the included reviews or meta-analyses reported outcomes such as adverse events, mortality, downstream diagnostic testing rates, quality of life or patient experience.

AI-estimated CT-FFR in NHSScotland and NHS England

In 2021, NHS Western Isles became the first health board in Scotland to routinely use an AI enabled version of Heartflow to diagnose CAD through non-invasive calculations of CT-FFR.[36]

NHS Western Isles reports that Heartflow has helped avoid unnecessary invasive procedures, which typically involve patients travelling long distances for further investigation or treatment on the mainland. There are no cardiology consultants or permanent radiologists in the Western Isles.

A retrospective cohort study compared outcomes in patients who underwent CT-CA at NHS England hospitals before the introduction of Heartflow CT-FFR with outcomes in a cohort who underwent CT-CA after Heartflow CT-FFR became available.[37] The version of Heartflow used in this study is described as AI-augmented CT-FFR that used deep learning combined with CFD modelling to assess blood flow in coronary arteries. It is unclear whether using deep learning as one element of CT-FFR calculation can be definitively classed as AI-estimated CT-FFR, but because the data come from NHS England and the study reports relevant outcomes, we have included a brief description of the results.

During the study analysis period, 27 hospitals across NHS England introduced Heartflow. The study population consisted of 90,553 patients; 35,688 who had CT-CA before CT-FFR was available and 54,865 patients who had CT-CA after CT-FFR was available. Of the patients who had a CT-CA after the introduction of Heartflow, 7,863 (14.1%) had Heartflow CT-FFR analysis. The mean age of study participants was 58 years (SD 13). Approximately half the participants (51.9%) were male. The median follow-up was 1,211 days (3.3 years), with 98.1% of patients followed up for 2 years.

Results are presented in *Table 2*. After adjusting for baseline differences in patient comorbidities and other covariates, there was no statistically significant difference in all-cause mortality or cardiovascular mortality before and after the introduction of Heartflow CT-FFR at 2-years follow-up. The risk of a myocardial infarction was statistically significantly higher among patients in the Heartflow CT-FFR available group. Patients in the CT-FFR available group had a statistically significantly higher risk of having a PCI compared with the group in which CT-FFR was not available. The rates of ICA with and without revascularisation were statistically significantly lower in the CT-FFR available group.

Table 2: Results at 2-year follow-up in a retrospective cohort study evaluating the rollout of Heartflow CT-FFR in NHS England[37]

Outcome	n patients (no CT-FFR)	n patients (CT-FFR available)	adjusted hazard ratio (HR) (95% CI)	p value
All-cause mortality	1,134	1,612	1.00 (0.93 to 1.08)	0.97
Cardiovascular mortality	465	617	0.96 (0.85 to 1.08)	0.48
Myocardial infarction	425	704	1.18 (1.05 to 1.34)	0.006
PCI	1,912	3,161	1.09 (1.03 to 1.15)	0.002
Coronary artery bypass graft (CABG)	691	1,020	1.01 (0.91 to 1.11)	0.89
All ICA	5,720	8,183	0.93 (0.90 to 0.97)	<0.001
ICA (no revascularisation)	3,117	4,002	0.84 (0.80 to 0.88)	<0.001

Summary of economic evidence

At present, we cannot draw any conclusions about the cost effectiveness of AI-estimated CT-FFR because of the lack of relevant published and empirical evidence.

- There were no published economic evaluations on AI-estimated CT-FFR in patients who had undergone a standard CT-CA.
- Previous NICE and SHTG advice only included cost or cost-effectiveness evidence on the non-AI version of Heartflow.
- No published data were found for NHSScotland health boards that have been using Heartflow (the AI or non-AI versions).

Future economic evaluations should be based on data from NHSScotland, including costs, workforce impact and patient outcomes after AI-estimated CT-FFR.

Patient experience

We did not find any studies that evaluated patient or user experience of AI-estimated CT-FFR.

Conclusions

Compared with invasive FFR measurement (the gold standard test for coronary stenosis), both AI-estimated and CFD-based CT-FFR demonstrated good diagnostic performance, with specificity values between 0.83 and 0.87. A non-invasive test with diagnostic performance equivalent to the invasive gold standard (invasive FFR) has the potential to reduce the number of patients undergoing unnecessary invasive diagnostic procedures. None of the included systematic reviews and meta-analyses examined the effect of AI-estimated CT-FFR on subsequent diagnostic pathways, nor did they report outcomes related to mortality, adverse events, quality of life or patient experience.

AI-estimated CT-FFR offers faster processing times compared with CFD-based CT-FFR, with the potential to allow for quicker clinical decision making, but the current evidence does not support any conclusions regarding the incremental value of CT-FFR estimation (ML or CFD) over CT-CA alone. The interpretation of the evidence on AI-estimated CT-FFR is constrained by high heterogeneity in the meta-analyses, use of retrospective designs in most primary studies, use of different functionally significant FFR stenosis thresholds and concerns about risk of bias in primary studies.

We were unable to find any published evidence on the cost effectiveness of AI-estimated CT-FFR. Economic evaluations from an NHS perspective are needed to support decisions on the value for money of this technology. There is also a need for UK and Scottish data from health boards that have trialled AI-estimated CT-FFR to help us understand the cost and resource implications of non-invasive CT-FFR for NHSScotland.

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Healthcare Improvement Scotland development team

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- Lucinda Frank, Senior Project Officer
- Jenny Harbour, Health Services Researcher
- Meryl Heggeland, Health Economist
- Charis Millar, Health Information Scientist
- Aishwarya Tewary, Health Economist

What is an Innovative Medical Technology Overview (IMTO)?

An IMTO provides a high-level summary of health and care innovations. IMTOs include a description of the technology and its potential use in Scotland, and an overview of the evidence to help gauge the potential impact of the technology on people and health and care services.

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Appendix 1: Abbreviations

AI	artificial intelligence
AUC	area under the curve
CABG	coronary artery bypass graft
CAD	coronary arterial disease
CFD	computational fluid dynamics
CHD	coronary heart disease
CI	confidence interval
CT	computed tomography
CT-CA	computed tomography coronary angiography
CT-FFR	computed tomography fractional flow reserve
DOR	diagnostic odds ratio
FFR	fractional flow reserve
ICA	invasive coronary angiography
IHD	ischaemic heart disease
IMTO	innovative medical technologies overview
ML	machine learning
NHS	National Health Service
NICE	National Institute for Health and Care Excellence
PCI	percutaneous coronary intervention
QUADAS-2	quality assessment of diagnostic accuracy studies version 2
SIGN	Scottish Intercollegiate Guidelines Network
SCAP	Scottish Cardiac Audit Programme
SD	standard deviation
SHTG	Scottish Health Technologies Group
UK	United Kingdom