ESC European Society of Cardiology

European Heart Journal (2024) **00**, 1–15
https://doi.org/10.1093/eurheartj/ehae415

STATE OF THE ART REVIEW
Digital health and innovation

Artificial intelligence-enhanced patient evaluation: bridging art and science

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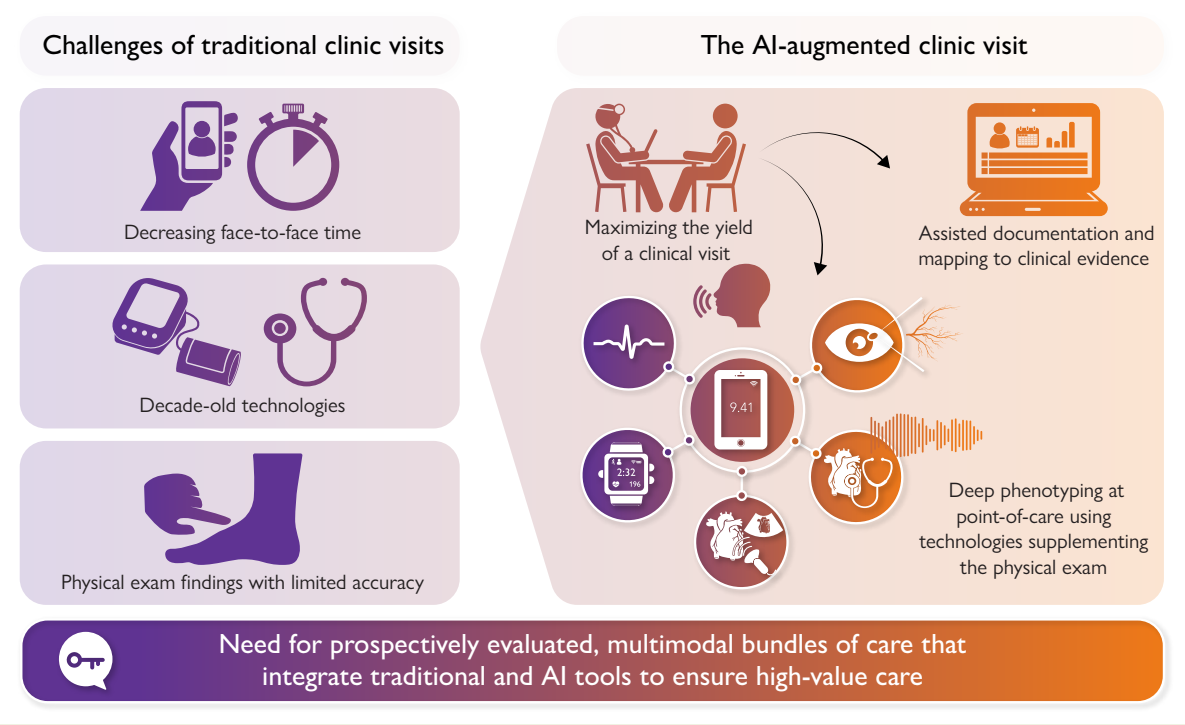
Received 11 February 2024; revised 23 April 2024; accepted 18 June 2024

Graphical Abstract



Bridging the art of traditional clinical evaluation with data-driven insights from new artificial intelligence-enabled digital approaches. AI, artificial intelligence

Abstract

The advent of digital health and artificial intelligence (AI) has promised to revolutionize clinical care, but real-world patient evaluation has yet to witness transformative changes. As history taking and physical examination continue to rely on long-established practices, a growing pipeline of AI-enhanced digital tools may soon augment the traditional clinical encounter into a data-driven process. This article presents an evidence-backed vision

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of how promising AI applications may enhance traditional practices, streamlining tedious tasks while elevating diverse data sources, including AI-enabled stethoscopes, cameras, and wearable sensors, to platforms for personalized medicine and efficient care delivery. Through the lens of traditional patient evaluation, we illustrate how digital technologies may soon be interwoven into routine clinical workflows, introducing a novel paradigm of longitudinal monitoring. Finally, we provide a skeptic's view on the practical, ethical, and regulatory challenges that limit the uptake of such technologies.

Keywords Artificial intelligence • Digital health • Remote monitoring • Health technology • Clinical decision support

Introduction

The rapid rise of artificial intelligence (AI) applications in medicine has fuelled hopes for more efficient healthcare delivery pathways capable of improving the experience of patients and clinicians.[1] However, despite the magnitude, pace, and scale of innovation,[1–4] the day-to-day clinical practice has hardly evolved over the last decades. With high rates of clinician burnout driven in part by digital tools that have failed to reduce clinical workload [i.e. electronic health records (EHRs)][5,6] and a growing physician shortage,[7,8] there is often a discrepancy between the pace of technological advancements and the experience of the cardiovascular workforce.

Here, we provide an overview of promising, evidence-based AI technologies that seek to transform the traditional art of patient evaluation into a process that blends clinical expertise with data-driven insights. Inspired by the latest scientific breakthroughs, we identify AI-informed care practices that might be efficiently integrated into existing workflows to synergistically improve the precision, effectiveness, safety, and speed of healthcare delivery. Focusing on their clinical implementation from the lens of a traditional clinical encounter built around the pillars of history taking and physical examination, we review the most notable advances that may effectively augment our ability to deliver patient-centred care while also covering frequently overlooked practical, ethical, and regulatory concerns (*Graphical Abstract*).

> **A new referral**: *Ms M. is a 66-year-old woman with hypothyroidism referred for increasing dyspnea on exertion over the last 3 months, intermittent leg swelling and weight gain. She takes no medications other than levothyroxine. A scanned copy of her electrocardiogram (ECG), attached to the consultation request, shows normal sinus rhythm, PR prolongation of 212 ms, and an incomplete left bundle brunch block with a QRS duration of 108 ms. She lives in a rural location, 2 hours away.*

Artificial intelligence-guided in-office clinical evaluation

Over many centuries, clinicians have refined the art of patient evaluation based on the pillars of history and physical examination. Despite this, modern clinical workflows remain prone to errors.[9–12] Information overload is often cited as a frequent cause of medical errors,[13,14] an important consideration for the cardiovascular workforce that is called to integrate large amounts of multimodal data and medical evidence. This underscores the need to design efficient AI systems that facilitate high-value care without further increasing the workload of clinicians (*Figure 1* and *Table 1*). Such systems may be multimodal and able to capture traditional (i.e. inspection and auscultation) as well as previously untapped sources of phenotypic information (i.e. gait, posture, and speech) at the bedside, thus maximizing and standardizing the information yield of a clinical visit through smart, yet low-cost digital interventions.

Artificial intelligence-assisted medical interview: from speech content to speech characteristics

With the expanded use of EHRs and an increase in documentation requirements around 35% of a clinician's time is spent in front of a screen.[52–54] Automatic dialogue summarization, which combines speech transcription along with computational linguistic approaches,[55] as well as intelligent clinical note-taking interfaces that combine audio-capturing and note-taking devices for dynamic note generation[56] may maximize face-to-face time during a clinical encounter, a key component of patient satisfaction.[57,58] Indeed, an ambient AI scribe system deployed across a US-based health system was successfully used in more than 300 000 encounters within the first 10 weeks of its implementation, with favourable user reviews and significant time savings.[59] Large language models (LLMs), such as ChatGPT, may further enhance communication between patients and their providers by adapting the relatively complex language often found in medical documents such as consent forms to the health literacy level of each patient.[60]

Of note, there might even be augmentation beyond easing up the cognitive demands during the clinical encounter, through emerging diagnostic modalities. Advances in signal processing technologies enable medically valuable information to be extractable not just from the patient's speech content but also from its characteristics. For instance, following years of research in neurodegenerative diseases,[61,62] speech feature analysis has shown promise in cardiology by flagging biometric fluctuations in response to fluid status changes, such as those seen in patients with heart failure (HF) through portable devices.[40,41]

Artificial intelligence-enhanced inspection

Pose and gait estimation

Inspection, the first pillar of the traditional physical exam, can offer a global perspective on the health and wellness of a patient[63] but may be limited by subjectivity. For instance, clinical frailty, an important determinant of overall health and prognosis,[64] is traditionally quantified using operator-dependent scales.[65] A series of studies suggest that AI-guided sensor-based gait analytics can provide standardized and reproducible metrics of frailty status,[15–17] directly correlating with long-term prognosis in patients with HF.[17] More recent technologies utilize Wi-Fi antennas to track pose and gait, thus enabling tracking of human motion using existing infrastructure,[66] possibly across inpatient, ambulatory, and community locations, often using device-level (or edge) computing that preserves patient privacy. Such standardized metrics may, in theory, evolve into valuable adjuncts in personalizing the risk/benefit of interventions such as anticoagulation and assessing quality of life.

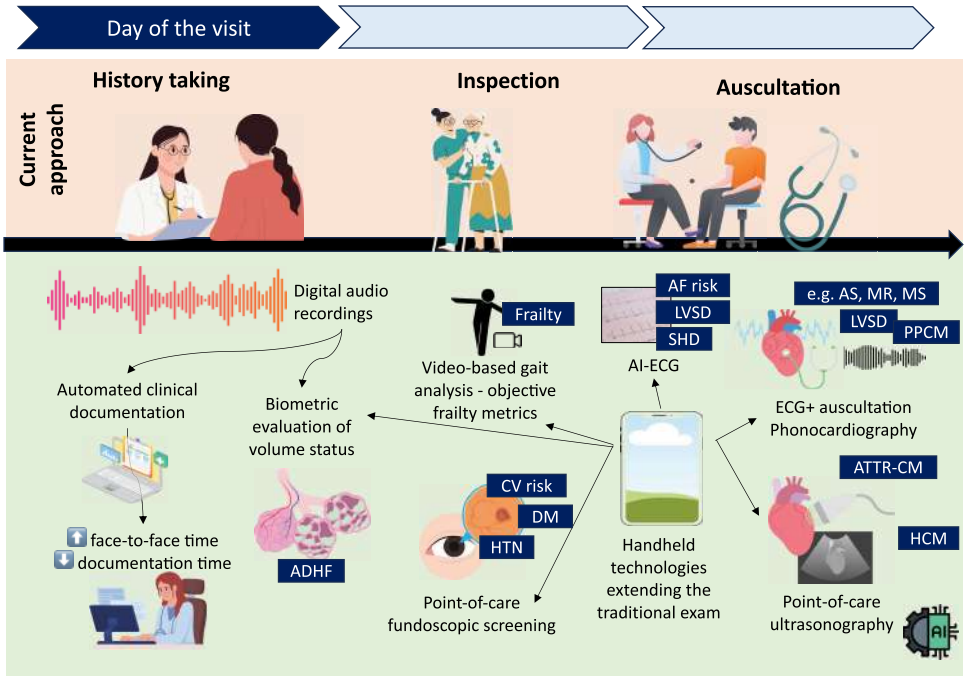

Figure 1 Artificial intelligence-enhanced clinical encounter and evaluation. Top: The traditional sequence of a clinical encounter encompasses a focused interview/history taking, followed by physical examination that includes inspection and auscultation, among others. Bottom: A visual summary of how artificial intelligence-based, digital approaches may augment this process, automating laborious tasks, improving our precision to detect signs of cardiovascular disease, and ultimately offering the promise of precision phenotyping at the point of care through handheld and portable devices. ADHF, acute decompensated heart failure; AF, atrial fibrillation; AI, artificial intelligence; AS, aortic stenosis; ATTR-CM, transthyretin amyloid cardiomyopathy; CV, cardiovascular; DM, diabetes mellitus; HCM, hypertrophic cardiomyopathy; HTN, hypertension; LVSD, left ventricular systolic dysfunction; MS: mitral stenosis; MR, mitral regurgitation; PPCM, peripartum cardiomyopathy; SHD: structural heart disease.

Artificial intelligence-guided interpretation of inspection findings

Various signs detectable on a routine inspection, such as xanthomas,[27] or even a diagonal earlobe crease (Frank's sign),[28] have been linked to an elevated risk of coronary artery disease (CAD). Moving one step further, recent studies have built convolutional neural network (CNN) algorithms that can discriminate the presence of CAD on coronary computed tomography angiography[29] and risk factors such as hypertension or diabetes,[67] directly from facial photos or full body photographs.[29,67] Many of these features are likely proxies for major atherosclerotic cardiovascular disease risk factors, including age and sex, and may be limited by questionable generalizability across different ethnic and racial populations.

Bringing back fundoscopy to the physical exam

Despite the breadth of evidence linking retinal phenotypes to cardiovascular disease, fundoscopy remains a forgotten art for many non-ophthalmology providers.[30] A fundoscopic exam was documented in just ~12% of primary care encounters even among patients with diabetes and had an estimated sensitivity of less than 14.9% in detecting diabetic retinopathy.[31] As opposed to deep learning analysis of facial photographs, AI-guided fundoscopy may represent a more reliable approach for the screening of cardiovascular disease. This is backed by robust evidence showing the feasibility of smartphone-based acquisition[32] and the downstream ability to detect a range of cardiovascular risk factors, such as smoking and systolic blood pressure, as well as composite cardiovascular risk estimates.[33–35,68]

Digital technology-guided assessment of congestion and hypervolemia

Inspection of jugular venous pulsations (JVPs) and of lower extremities for pitting oedema represent rapid techniques to estimate central venous pressure (CVP) and volume status. However, in an analysis of 217 patients in the emergency department, hepatojugular reflux and jugular vein distention had 69% sensitivity and 28% specificity in detecting CVP above 5 mmHg.[36] A series of computer vision models have been developed to automate the detection of JVP by using photoplethysmography (PPG)[37] or by detecting skin deformations using a sub-pixel registration algorithm and camera.[38] Furthermore, a recent case report described using a camera to automatically extract and compare real-time images of the extremities to standard anatomical models. This could provide personalized, observer-independent metrics of oedema,[69] which is otherwise limited by poor inter-rater agreement.[39]

Artificial intelligence-enhanced auscultation

Since the invention of the stethoscope in 1816 by Laennec, this simple yet powerful device has been at the forefront of cardiovascular diagnostics.[70] However, mastering the identification of murmurs comes with a

Table 1 Examples of digital health tools that might augment the traditional physical exam

Physical exam	Current limitations	Proposed digital automation
Frailty assessment	• Subjective • In-clinic assessment may not reflect longitudinal trends	ML-guided gait sensors[15–17] or smartwatches[16] seek to provide standardized frailty metrics
Blood pressure	• Single snapshot in time that may not reflect longitudinal trends or capture subclinical disease or paroxysmal episodes	Wearable cuff-less blood pressure devices for longitudinal monitoring in the community[18–21]
Pulse assessment		Wearable devices for continuous rhythm, activity monitoring in the community[22–26]
Physical inspection signs	• Subjective and often missed (e.g. xanthomas) • Imprecise (e.g. Frank's sign)[27,28]	CNN-based computer vision models applied to photos (e.g., facial or other) may flag coronary artery disease risk[29]
Fundoscopic exam	• Rarely performed • Steep learning curve[30,31]	Smartphone-adapted computer vision models can enable retinal image acquisition with direct inference to uncover hidden CV labels at the point of care[32–35]
Jugular venous pulsations	• Poor agreement • High inter-rater variability[36]	Digital camera- or photoplethysmography-based technologies to automate the characterization of jugular venous pulsations[37,38]
Lower extremity oedema	• Subjective assessment • Often hard to compare with baseline[39]	Computer vision-enabled comparison of images to personalized anatomical models for longitudinal tracking[39]
Volume status exam	• Assessment frequently relies on multiple aspects of history and physical examination	Supplementing weight tracking and physical exam with other readily available information, including speech-based analytics[40,41]
Auscultation	• Inter-rater variability • Steep learning curve • Sub-optimal accuracy • Disparities in diagnosis exacerbated by poor access to echocardiography[42–44]	Digital stethoscopes[45] or smartphone-adapted phonocardiography applications[46] for standardized recording and processing ECG-enabled stethoscopes to assist diagnostic inference by supplementing auscultation findings with AI-ECG tools[47,48] Point-of-care ultrasonography at scale to supplement auscultation findings at the point of care,[49,50] also using wearable ultrasonic imager patches[51]

AI, artificial intelligence; CAD, coronary artery disease; CNN, convolutional neural network; CV, cardiovascular; ECG, electrocardiography; ML, machine learning.

steep learning curve, and inter-rater agreement is highly variable across training levels.[42–44] For example, real-world agreement between phonocardiographic findings and expert-level interpretation of an S3 sound is, at best, modest, with a kappa of 0.37 and estimated sensitivity of up to 52%.[44]

AI-enhanced auscultation in the form of digital stethoscopes can be valuable in standardizing both the acquisition and interpretation process. For instance, it enables reliable remote auscultation in congenital heart disease (96% accuracy vs. 97% for face-to-face evaluation)[71] and can automate the detection of moderate-to-severe aortic stenosis (AS)[45,72] and mitral regurgitation.[45] These findings extend to AI-guided lung auscultation, where accuracy may exceed that of trainees.[73] We anticipate that the scalability of these tools in the community will increase further as they are adapted for smartphone use. In a study of 1148 users contributing 7597 recordings, more than four in five users successfully obtained at least one recording using a smartphone-adapted application, with three in four recordings characterized by good quality.[46]

Artificial intelligence-guided electrocardiography

Although not a part of the traditional physical exam, 12-lead ECG and point-of-care echocardiography are increasingly performed at the point of care, boosted by AI-assisted inference.[74] One of the earliest landmarks was the development of ECG-based CNNs that reliably discriminated left ventricular systolic dysfunction (LVSD) from 12-lead ECG signals and images.[75–77] When tested in a prospective, cluster-randomized clinical trial across outpatient primary care teams, AI-ECG-based screening resulted in a 32% higher rate of diagnosing LVSD without significantly increasing the rates of echocardiography referral compared with standard care.[78] Other applications have shown that AI-ECG may also screen for occult atrial fibrillation using ECG recordings obtained in normal sinus rhythm,[79,80] as well as other structural and valvular cardiomyopathies, including AS,[81–83] hypertrophic cardiomyopathy,[84–86] cardiac amyloidosis,[87] allograft rejection in heart transplant recipients,[88] electrolyte abnormalities at the point of care,[89] acute life-threatening conditions such as acute myocardial infarction,[90] and can further provide insights into left ventricular filling pressures,[91] and right ventricular function.[92]

A potential limitation in the scalability of these tools is their reliance on signal-level data that are rarely available to the end-user. To this end, AI models have been adapted for use with ECG images (acquired at the point of care using any smartphone) with state-of-the-art performance for a range of rhythm and conduction abnormalities, as well as hidden label detection such as LVSD and hypertrophic cardiomyopathy.[76,93–95] Furthermore, several tools can be adapted for single-lead acquisition with excellent performance for hidden labels such as LVSD,[47,96,97] thus making them compatible with commercially available portable, handheld, or wrist-worn devices. Single-lead AI-ECG algorithms can also be coupled with digital stethoscopes, enabling simultaneous

acquisition of heart sounds and ECG recordings. This was tested in a prospective cohort of 1050 patients referred for echocardiography in the UK, with ECG-enabled stethoscopes reliably discriminating LVSD with an area under the receiver operating characteristic curve (AUROC) of up to 0.91.[47] This paves the path for scalable global health applications, as done in the SPEC-AI Nigeria study, where AI-ECG tools were tested against the local standard of care for the screening of peripartum cardiomyopathy.[48]

Adding a new pillar to the physical exam: artificial intelligence-guided insonation

With the expanding availability of handheld ultrasound devices and a renewed focus on ultrasound education, ultrasonography is considered the next pillar of the modern physical exam.[98] Artificial intelligence tools can assist novices in acquiring standard echocardiographic views of good diagnostic quality (up to 98.8% accuracy for left ventricular size, function, and pericardial effusion when tested by eight nurses scanning 30 patients),[49] paving the path for scalable deployment across international locations.[50] Automated systems not only provide real-time interpretation of LVEF with accuracy matching that of human experts[99] but also may enable efficient screening of valvular disease, such as AS, through deep learning-guided interpretation of 2D echocardiography without Doppler, thus expanding the potential of handheld devices.[100,101] A noteworthy innovation in this space is a newly designed wearable ultrasonic patch that can efficiently attach to the skin and provide interpretable videos of left ventricular function with direct estimation of volumes and the ejection fraction.[51] Subsequent iterations of this nascent technology across ambulatory settings may enable efficient phenotyping by following a process that is as simple as attaching an ECG lead.

> **The day of the visit:** *Ms M. presents for her clinic visit. A secure, closed-loop, voice-recognition and video system produces a summary of the discussion. An automated gait-assessment tool suggests a high frailty score, and Ms M. shares that she has been experiencing worsening neuropathy with two falls in the preceding year. An ECG-based screen applied to the scanned copy of her ECG demonstrates a high risk for atrial fibrillation and an elevated risk of cardiac amyloidosis. A digital stethoscope captures a systolic ejection murmur with decreased S2 intensity, consistent with an AS murmur, and a copy is stored for future reference. This prompts an AI-POCUS assessment with the AI classifier flagging likely moderate-severe AS. A voice-based recognition system coupled with a smartphone-enabled video assessment of JVP also supports the physical exam consistent with hypervolemia. She is referred for further evaluation, which includes a complete transthoracic echocardiography and an event monitor, diuresis, and further medication titration plans. Before leaving, Ms M. asks you about the utility of using a smartwatch or other device to track her health while at home.*

After the visit: artificial intelligence-assisted remote monitoring

Perhaps the greatest potential of AI in revolutionizing patient care lies in enabling smooth transitions between in-office and remote monitoring through the timely recognition of changes in a patient's clinical trajectory.[102] This care paradigm is well suited for specific patient populations, such as patients with HF who may experience rapid changes in their clinical trajectory.[103,104] However, it may also extend to primary prevention, where wearables may paint a more accurate picture of longitudinal cardiovascular health (*Figure 2*).

Remote fluid monitoring

Ambulatory monitoring of patients with HF has been made feasible through the development of implantable pulmonary artery pressure sensors, which effectively decrease the risk of recurrent hospitalizations in patients with moderate-to-severe HF.[105,106] However, the invasive nature of such devices also underscores the need for more scalable technologies. An emerging non-invasive toolkit now includes platforms analysing the effects of volume status on vocal cord mechanics,[40] as well as 3D-image-based sensors that enable an objective assessment of lower extremity oedema changes.[69] Similarly, a remote dielectric sensing approach that uses low-power electromagnetic signals emitted across the thorax may correlate with total lung fluid estimates through chest computed tomography,[107] whereas smartphone-enabled seismocardiography may discriminate patients with HF from controls by quantifying cardiac-induced vibrations at the surface of the chest.[108]

Smartwatch-based remote rhythm monitoring

The scalability of smartwatches in tracking cardiovascular biometric signals has been eloquently illustrated across large-scale studies.[22,23] In the Apple Heart study,[22] 419 297 participants without known atrial fibrillation consented to monitoring for irregular heart rhythm using their smartwatch, followed by confirmation by patch ECG. Over a median of 8 months, 1 in 200 participants received such an alarm; among those who returned an ECG patch recording, 34% had evidence of atrial fibrillation, with a positive predictive value of 0.84.

Despite this experience, the scalability of smartwatches merits some key considerations. First, performance can vary substantially across different manufacturers and models.[109] Inconclusive ECG strips due to noise are common,[109] although noise-adapted models are feasible and may boost resilience and robustness.[96] Second, from a behavioural standpoint, detecting subclinical arrhythmias may not necessarily result in risk factor modification. In a prospective study of 60 629 patients in Belgium who participated in remote smartwatch-based monitoring for 8 days, 791 (1.3%) were diagnosed with atrial fibrillation.[110] While a positive screen was associated with an increase in the use of anticoagulation, there was no significant change in risk factor modification strategies among those with subclinical atrial fibrillation.[110] Third, while scalable screening may increase community awareness and prompt timely referrals and work-up, low prevalence in relatively healthy populations could translate into low positive predictive values and high rates of false-positive alerts.

Wearables: beyond rhythm monitoring

The value of smartwatch technologies extends beyond rhythm monitoring to the assessment of physical activity levels,[24–26] objective quantification of frailty status,[16] and hidden disorders, i.e. those not discernable on expert evaluation of the same data sources.[111,112] These include LVSD, as demonstrated in prospective and retrospective studies,[96,97] with an AUROC of ~0.88 for detecting concurrent cardiomyopathy with reduced left ventricular systolic function among individuals with at least one watch-classified sinus rhythm ECG within 30 days of an echocardiogram.[97] While these models traditionally rely on single limb lead signals, new approaches may enable the direct acquisition of precordial lead signals on smartwatches, thus paving the path

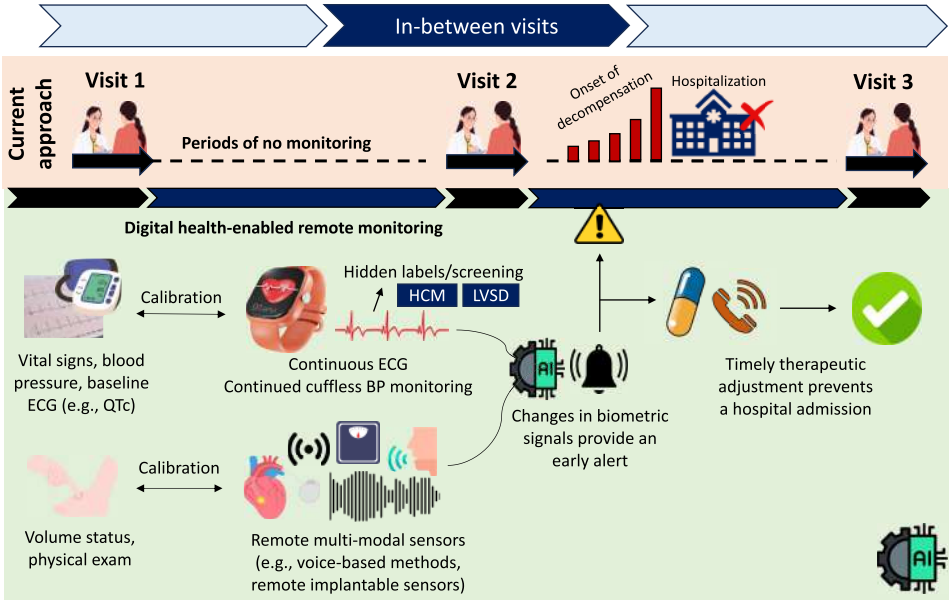

Figure 2 Artificial intelligence-guided and digital health-enabled remote monitoring. Top: Traditionally, in-person clinic visits have been separated by long periods with lack of remote monitoring. Such intervals represent high-risk periods for decompensation given that changes in a patient's clinical trajectory may not be detected in a timely fashion to prompt appropriate adjustments in medical therapy. Bottom: Several new digital tools adapted to various signal modalities (single-lead electrocardiography and voice-based features), ranging from wearable devices to portable or implantable sensor, directly calibrated against in-office measurements, now enable remote monitoring in the community. These digital solutions may function as an extension of the physical exam and clinical assessment, with in-person clinical visits reserved for regular recalibration of remote readings. AI, artificial intelligence; BP, blood pressure; ECG, electrocardiography; HCM, hypertrophic cardiomyopathy; LVSD, left ventricular systolic dysfunction

for point-of-care 12-lead ECGs.[113] Applications that detect ST-segment changes,[114] or QTc prolongation,[115] further highlight how ambulatory use of such technologies could soon screen for myocardial ischaemia during everyday activities, or guide safer medication titration. Multiplatform AI toolkits are also available to ensure broad compatibility across wearable manufacturers and efficient and secure data transmission with personalized inference in the community.[116] Finally, advances in material engineering may embed such ECG capabilities into everyday items, such as ECG-enabled 'smart clothes'.[117,118]

Cuffless blood pressure systems

Blood pressure is dynamic, with beat-to-beat systolic blood pressure varying substantially depending on intrinsic and extrinsic factors.[119] Similar to ECG, wearable, cuffless systems overcome the discomfort of traditional sphygmomanometer-based methods and paint a more complete and personalized to guide precise treatment.[18] A range of devices exist, including AI-powered PPG systems,[19] which offer good agreement with gold-standard sphygmomanometer devices,[20] as well as bio-impedance sensor arrays built-in flexible wristbands that can be worn as wristwatch-like devices.[21] Nevertheless, in most cases, further validation and calibration are needed before their broader use.

> **Tracking health status in-between visits:** *Ms M. returns home. Every morning, she records a 5-s message on her smartphone that, combined with close weight monitoring, allows her to closely titrate her oral diuretics. She completes her echocardiogram, which shows moderate left ventricular hypertrophy with preserved function, biatrial enlargement, and moderate aortic stenosis. Her wristwatch, connected to a secure platform, identifies a substantial (~21%) burden of atrial fibrillation while also recording a decrease in her activity levels and daily steps over the preceding 3 months, with marked diurnal variation in her systolic blood pressure. She returns for a follow-up appointment with this information automatically loaded and summarized.*

Dynamic longitudinal assessment through personalized digital phenotypes

The in-depth evaluation of a clinical case and effective care transitions between different clinicians requires thoughtful integration of prior objective data with new information and evidence collected during subsequent clinical encounters (*Figure 3*).

Artificial intelligence for medical record summarization

Artificial intelligence models are increasingly used to process longitudinal data from EHRs for diagnostic and prognostic purposes.[120] In two small proof-of-principle simulation studies, AI-based computer-generated textual summaries and optimized records enabled clinicians to identify key information, resulting in up to 18% faster review times and positive participant responses.[121,122] We anticipate that the

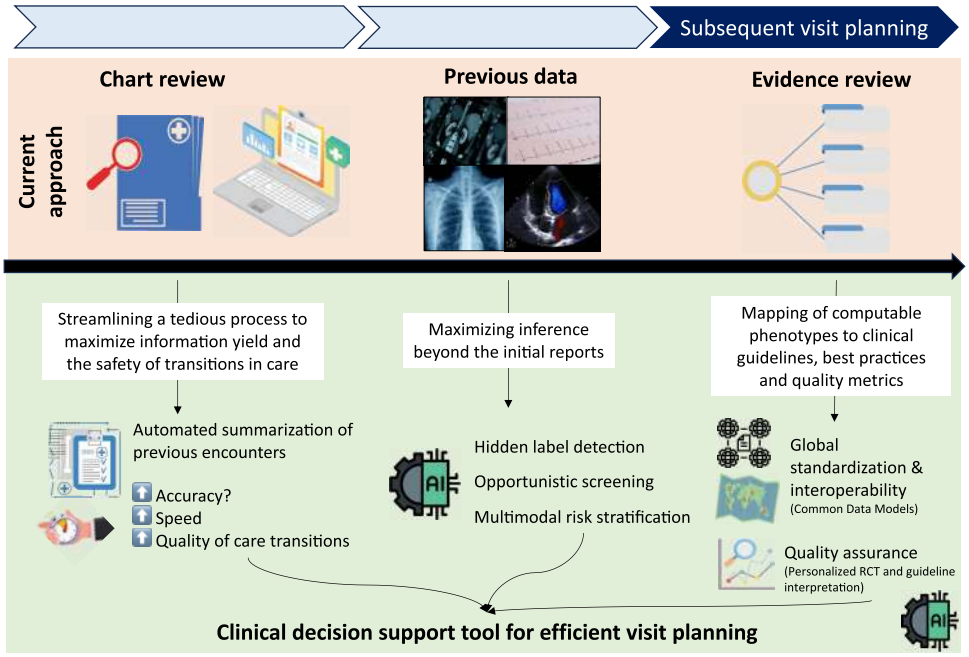

Figure 3 Artificial intelligence-enhanced chart review and visit planning. Top: Overview of the steps that traditionally preceded a clinical encounter, including (i) review of existing records, structured (clinical notes, etc) and unstructured data (imaging studies and electrocardiograms) as well as (ii) mapping of key complaints and anticipated problems to existing guidelines and evidence. Bottom: optimization of each step using artificial intelligence and computational platforms for clinical assistance or deeper/hidden label inference. RCT, randomized clinical trial

increasing adoption of common data models (CDMs) and LLMs will further boost these capabilities. Common data models represent database schemas that codify uniform data standards to boost collaboration across distinct settings.[123] Such tools have already been used across national EHR sources in the UK to map 216 million encounters from 502 536 patients with HF,[124] as well as in the UK Biobank,[125] and across other European countries such as Germany.[126] Successful deployment of CDMs across borders could simplify many clinician tasks, from automating clinical trial eligibility surveillance and trial referrals,[127,128] to increasing diversity and representation in clinical trials, as well as enabling benchmarking of care practices.[129] Furthermore, LLMs, made popular through the wide adoption of ChatGPT, can acquire domain expertise through fine-tuning in medical data sets and instruction prompt tuning.[4] While early analyses showed that high-performing medical LLMs (e.g. Med-PaLM) were inferior to clinicians when evaluated for comprehension, knowledge, recall, and reasoning,[130] recent work hints towards conversational AI systems that may even be superior in diagnostic reasoning and communication skills than humans.[131]

Artificial intelligence for personalized planning of a clinical encounter

Structured patient phenotypes may enable direct mapping to existing clinical guidelines,[132–135] thus providing an important 'nudge' (reminder). When tested in a pragmatic randomized clinical trial, EHR-embedded alerts shown to providers caring for patients with HF with reduced ejection fraction resulted in significantly higher rates of goal-directed medical therapy at 30 days compared with standard care.[136,137] With increasing open access to large clinical trial data sets, it is also feasible to define computational phenotypes of personalized benefit directly from publicly available clinical trial data sets (*Figure 4*).[138–140] Such tools can be mapped to dynamic EHR phenotypes, thus providing personalized estimates of treatment effectiveness and guiding a more personalized, yet evidence-based discussion for each patient.[141]

This paradigm does not only apply to structured data but also extends to AI-guided interpretation of previously performed imaging studies,[142] beyond ECG, which was previously discussed. For instance, AI applications can leverage chest X-ray to screen for cardiovascular disease[143,144] and existing CT scans in a patient's record can be flagged for coronary calcifications[145,146] or previously unrecognized coronary inflammation.[147,148] Deployment of these tools within a digital environment tailored to cardiovascular risk factor risk modification may be an effective tool to enable providers to rapidly digest large amounts of data distilled into actionable nudges and recommendations.

> **Harnessing digital phenotypes:** *While preparing for the subsequent patient's visit, an EHR-embedded, customized LLM application provides an automated narrative review of the patient's interim course and outpatient visits within 5 seconds. As has now become routine, computer vision models were deployed to previously obtained imaging, marking the presence of dense coronary calcifications on a remote non-contrast CT scan of the chest. Based on her history and echocardiography findings further testing is initiated to rule out amyloidosis and initiate a risk-benefit discussion about anticoagulation based on subjective accelerometer-derived frailty metrics.*

Although this example aims to provide an overview of how digital health applications can supplement the art of patient evaluation with standardized, data-driven insights, several practical, methodological, regulatory, and ethical considerations may limit their use.[149,150]

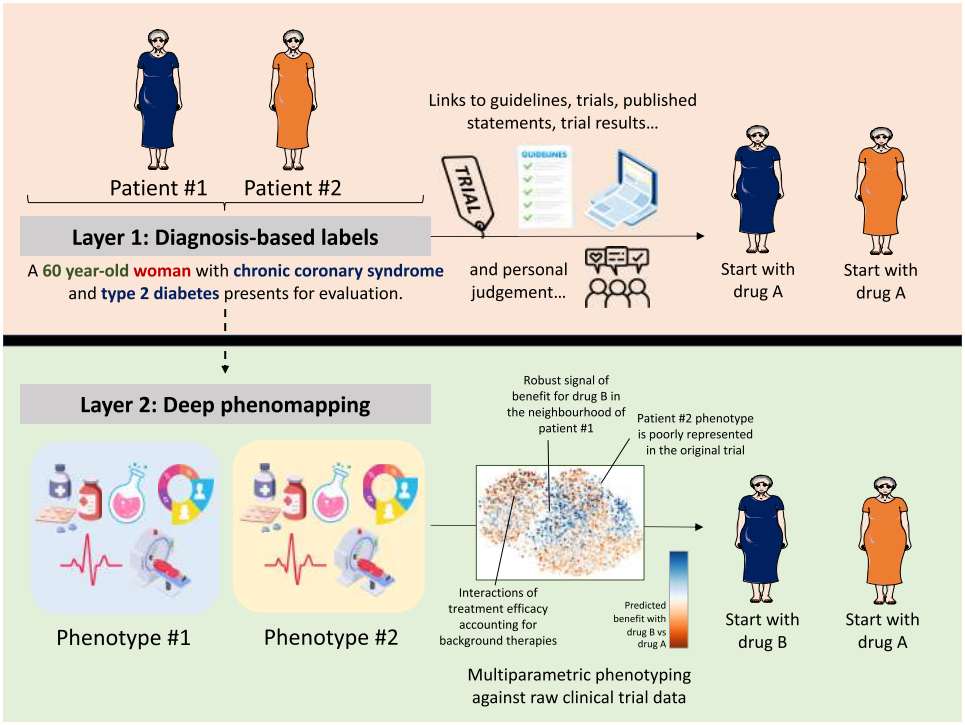

Figure 4 Extending clinical knowledge and experience through data-driven phenomapping. To facilitate investigation, communication, and collaboration, clinical phenotypes are clustered at the highest level into diagnoses and linked codes, which are used to match clinical profiles to desired/recommended tests and treatments, relying on best evidence, guideline statements, and/or clinical judgement. However, this heuristic approach simplifies and therefore ignores the extent of phenotypic heterogeneity that is commonly seen within clinical trials and the real world. Machine learning-guided, iterative phenomapping approaches that can map individualized patient profiles to original clinical trial data, thus projecting estimates of individualized efficacy, safety, and representation, may be used to inform therapeutic-decision making, particularly where comparative effectiveness or best practices remain unclear

Key challenges: a skeptic's view on the digitization of medicine

Methodological limitations

Principles of good research practice and statistical and predictive modelling are essential for AI-based models.[151–153] However, these models are generally developed outside prospective real-world environments where humans may act on and modify input features. In a simulation study that included many scenarios where models were deployed sequentially, in parallel, or following re-training, there was a consistent drop in the effective accuracy of an AI-based prediction tool for acute kidney injury in critically ill adults with ongoing use.[154] This complex interaction between continuous signals and medical interventions highlights the need for critical assessment of the clinical workflows where AI models are deployed,[155,156] and systems that facilitate continuous feedback between key stakeholders to prevent performance degradation.[155]

Regulation and privacy

The importance of regulatory oversight, especially for intermediate- or high-risk devices, and the shortcomings of existing regulatory clearance pathways that rely heavily on equivalence to predicate devices have been extensively reviewed.[157–159] Not surprisingly, product characteristics that determine their regulatory fate, such as their performance metrics and explainability, also predict their real-world uptake.[160] Traditional tools, such as heatmaps that highlight key areas of an image or input signal, and also novel approaches, such as talk2model, a dialogue system that relies on natural language processing to interactively provide insights into a model's structure and predictions, could help increase trust and promote uptake.[161] Critically, emerging evidence suggests that clinicians provided with explainability information are often unable to act against the model's suggestions, even if the explainability suggests a failure of the model's performance.[162] This 'automation bias' will be essential to explicitly address by ensuring the quality of deployed models.[163]

The concept of regulation is closely intertwined with data privacy, especially for generative AI models that rely on large amounts of multimodal data.[164] Traditional strategies for data de-identification are often inadequate, especially when applied to image data, and LLMs have been known to release identifiable information through prompting.[165] Furthermore, while open sourcing of models boosts adoption and collaboration, when sensitive information is used for developing these models, they often need to remain within a protected environment.[166] Moreover, partnerships between healthcare, academic, and commercial entities are often essential to accelerate clinical deployment, yet this should not come at the cost of patient privacy. Federated learning approaches offer alternative ways of training models at scale without needing protected information to exit secure, local systems.[167] Regulatory authorities have recognized these concepts and

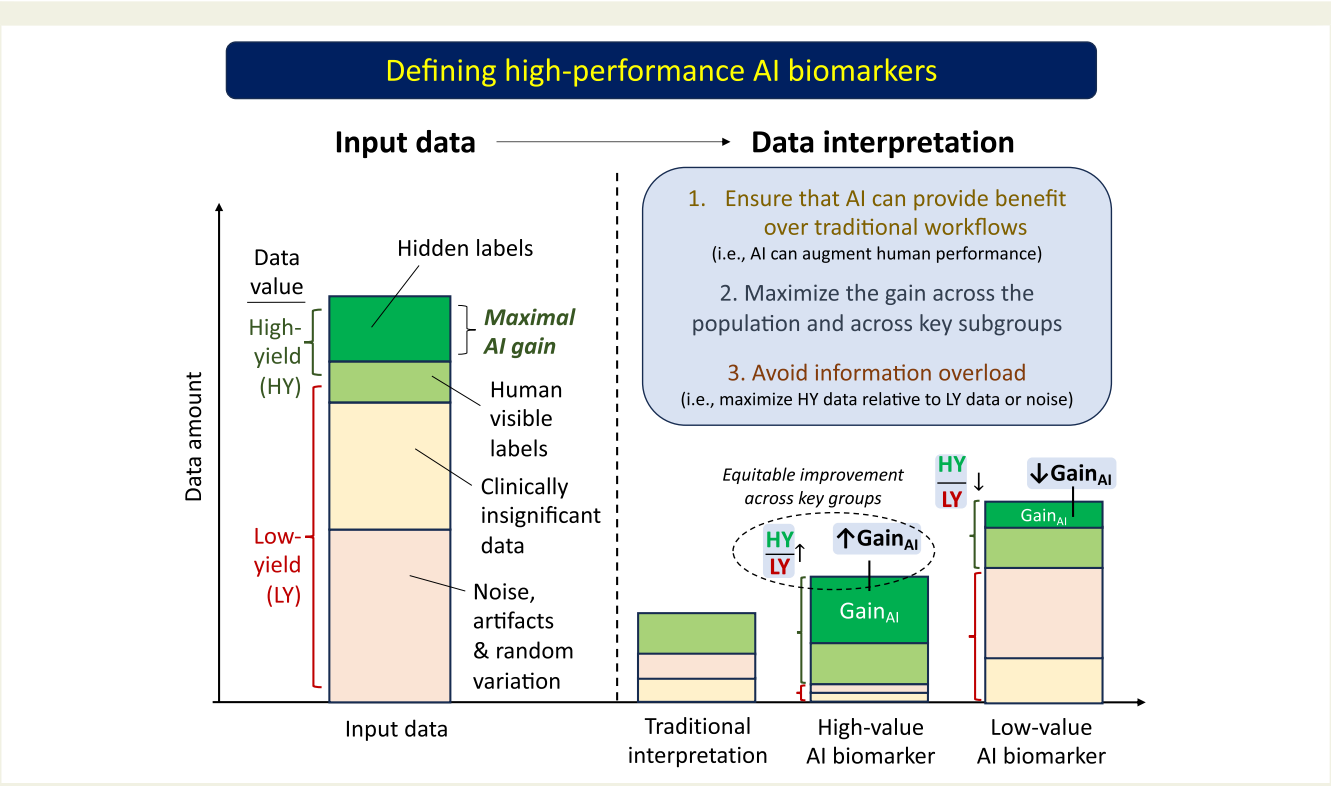

Figure 5 Principles of a high-performance artificial intelligence biomarker. Biomedical and clinical signals (electrocardiograms, imaging studies, and physical exam findings) contain large amounts of information, most of which reflect noise, random variation and carry no clinical significance. The art of interpreting these studies relies on distilling the minimal amount of clinically relevant information from these sources. Whereas clinical experience can maximize the labels that are recognizable by a human reader, hidden labels that remain invisible to the human expert enable artificial intelligence algorithms to augment human performance. In an ideal scenario, these biomarkers can identify such hidden labels and offer significant performance gains, while reducing the ratio of high- to low-yield information. This may maximize the achieved inference without contributing to information overload. AI, artificial intelligence; HY, high yield; LY, low yield

have been working on adapting existing data privacy regulations (i.e. General Data Protection Regulation in Europe and the Health Insurance Portability and Accountability Act [HIPAA] in the USA) accordingly.[168]

Equitable use and other ethical considerations

The common denominator across recent executive orders and procedures in Europe and the USA is the call to equitable and trustworthy AI that will benefit diverse populations.[169,170] However, bias in clinical model development can arise from many sources[171]; for instance, models may learn socio-demographic patterns associated with an outcome of interest through unmeasured confounders, thus perpetuating existing inequities[172,173] through 'algorithmic bias'.[171]

In the same vein, ethical concerns have been raised about the use of several remote or smartwatch-based screening methods that are directly available to consumers due to the lack of high-quality evidence about the downstream consequences of screening.[174] A recent survey also showed that even clinicians do not always agree on the management of smartwatch alerts.[175] Finally, as of 2020, a minority of all patients with or at risk of cardiovascular disease in the USA used smart devices (2 in 5) or wearables (1 in 4) to track their health goals, with persistently lower uptake among lower-income and older individuals.[176,177]

A key objective should be to promote AI-related literacy and education, targeting healthcare providers and the public. With a pace of innovation that exceeds our ability to track the underlying evidence, we need to reimagine medical diagnosis perhaps and care as an AI-assisted Bayesian process, where clinicians learn to critically review AI-generated evidence, updating their prior beliefs and using prior and new knowledge as reference marks to double-check the AI output.[178,179] While this discussion has raised concerns about skill atrophy,[163] it echoes decade-long concerns about the digitization of medicine and increased reliance on medical testing,[180] in what was recently described as a 'meta-clinical era'.[181] Rather than suppressing innovation, the focus should shift to optimizing the symbiosis of clinicians with new technologies while providing transparent metrics of model accuracy and uncertainty.[182]

Defining high-performance and high-value artificial intelligence strategies

With many new AI tools on the horizon, it is imperative to clearly define what constitutes *high-performance* (*Figure 5*) and *high-value* care (*Figure 6*). First, for diagnostic and prognostic biomarkers, it is important to determine whether and to what extent AI truly augments human performance without contributing to information overload. Second, AI systems should be studied prospectively to demonstrate real-world effectiveness. This critical step is essential to prevent medical device

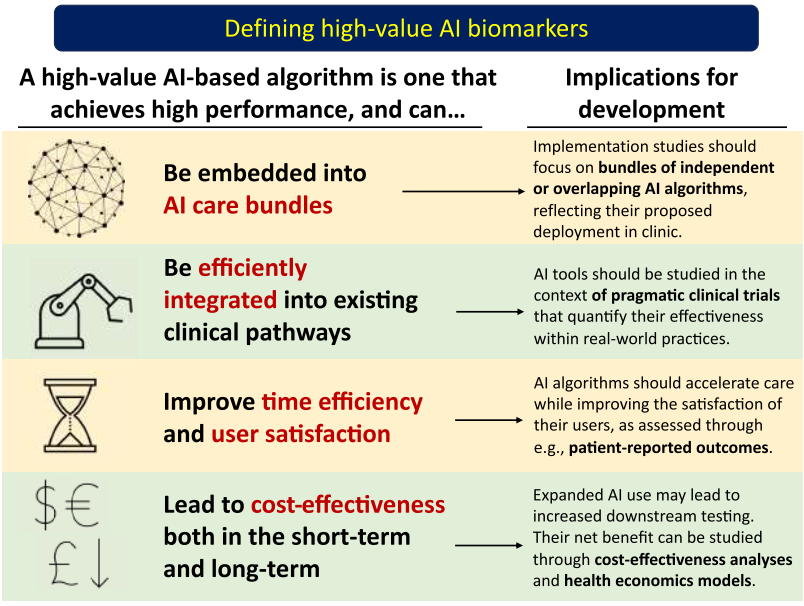

Figure 6 Defining a high-value artificial intelligence biomarker. For an artificial intelligence biomarker to contribute to high-value care, it needs to not only achieve high performance for its specified use (i.e. high discrimination, good calibration) but also (i) be easily integrated into a broader ecosystem of multiple artificial intelligence algorithms that will be used in parallel and may learn to work synergistically, (ii) be automated and adapted for real-world use within existing clinical pathways, thus boosting its eventual uptake, (iii) result in time savings and user satisfaction, and (iv) be associated with cost-effective care that accounts for possible increases in downstream testing and interventions, as well as patient anxiety through false-positives findings. AI, artificial intelligence

'bloat' and may motivate engineers and investigators to incorporate aspects of the clinical environment into the development process. For instance, given the vast number of AI-supported non-invasive solutions in HF, defining AI bundles that efficiently integrate multiple HF-directed sound-, video-, voice-, and other signal-based tools will ensure the in-depth evaluation of their synergistic or competing effects. Furthermore, continual learning approaches[183] may identify aging algorithms that no longer provide additive information and remove them from clinical use. Finally, AI interventions should be studied within pragmatic clinical trials to maximize generalizability, incorporating patient-reported outcomes,[184] objective time and cost-saving estimates, as well as safety signals arising from false-positive findings, which many result in alert fatigue,[185] patient anxiety, and unnecessary downstream interventions.[186]

Conclusions

In summary, we provide a roadmap for how the AI-led digital transformation of healthcare may augment a clinician's ability to deliver high-value care directly at the bedside through a diverse set of novel digital health technologies spanning the full spectrum of patient evaluation. We review how several digital tools may be used sequentially or in parallel to automate tedious tasks and augment diagnostic and prognostic inference through more granular and personalized assessment of multimodal health data streams. While the examples illustrated here may paint an ideal scenario where models interact seamlessly with existing care pathways, we also highlight key challenges that may eventually arise and how increasing awareness of these will be essential for the AI–human partnership to reach its full potential in cardiovascular medicine.

Declarations

Disclosure of Interest

E.K.O. is a co-inventor in patent applications US17/720,068, 63/619,241, 63/177,117, 63/580,137, 63/606,203, 63/562,335, WO2018078395A1, and WO2020058713A1. He has been an *ad hoc* consultant for Caristo Diagnostics Ltd and Ensight-AI, Inc., and has received royalty fees from technology licensed through the University of Oxford. R.K. is an Associate Editor of JAMA. He receives research support, through Yale, from Bristol-Myers Squibb, Novo Nordisk, and BridgeBio. He is a co-inventor of US Provisional Patent Applications 63/619,241, 63/177,117, 63/580,137, 63/606,203, 63/562,335, 63/428,569, 63/346,610, 63/484,426, and 63/508,315. E.K.O. and R.K. are co-founders of Evidence2Health, a precision health platform to improve evidence-based cardiovascular care. R.K. is an academic co-founder of Ensight-AI, Inc., an AI-ECG analytics company.

Data Availability

No data were generated or analysed for this manuscript.

Funding

The authors acknowledge funding through the National Institutes of Health (NIH) under awards 1F32HL170592-01 (E.K.O.), R01HL167858 and K23HL153775 (R.K.), and the Doris Duke Charitable Foundation under award 2022060 (R.K.). The content is solely the responsibility of the authors and does not necessarily represent the official views of the funders.

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