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# Applying artificial intelligence to support cardiovascular risk prediction in resource-constrained settings: qualitative insights from Indonesian doctors

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**ABSTRACT**

Cardiovascular disease (CVD) risk assessment underpins preventive care. Although machine learning models often outperform traditional risk prediction methods, adoption of artificial intelligence (AI)-based clinical decision support (CDS) tools remains limited, especially in resource-constrained settings. This study explored the sociotechnical context of CVD risk assessment in resource-constrained settings and identified potential applications for AI-based CDS. Semi-structured interviews were conducted with 27 Indonesian doctors, including general practitioners and cardiologists. Interviews examined clinical decision-making processes, challenges associated with resource constraints, and potential use cases for AI-based CDS. Data were analyzed using a deductive thematic approach informed by the SEIPS (Systems Engineering Initiative for Patient Safety) framework. Doctors reported managing high patient volumes, relying on paper-based medical records, and making largely subjective decisions due to limited access to confirmatory investigations and specialist support. Acute coronary syndrome resulting from atherosclerosis was identified as the most common and important clinical problem. Participants highlighted atherosclerotic cardiovascular disease (ASCVD) risk assessment as a promising application for AI-based CDS because it uses widely available clinical information and can support preventive care decisions. Implementation of AI-based CDS should be guided by local clinical needs and sociotechnical context. Further research is needed to evaluate effects on clinical decision-making and patient outcomes.

## Introduction

Cardiovascular disease (CVD) remains the leading cause of morbidity and mortality both in developed and developing countries (Leong et al. 2017). In addressing this global health challenge, doctors can employ clinical decision support (CDS) to enhance care delivery and patient outcomes through better risk assessment, diagnosis, and image interpretation (Groenhof et al. 2019; Lu, Melnick, and Krumholz 2022; Marcolino et al. 2021). Among CDS tasks, risk assessment underpins preventive care and remains challenging (Alba et al. 2017). As such, many individuals at risk routinely fail to be identified, while others who are not at risk are given preventive treatment unnecessarily.

Many current CDS are based on rules crafted by human experts; however, integrating machine learning (ML) into CDS provides new opportunities to incorporate complex relationships among numerous classic and novel risk predictors and their non-linear interactions. Additionally, ML-based CDS can be easily calibrated for different subgroups within a population. This not only enhances the accuracy of risk assessment but also addresses the issues of under diagnosis and over-treatment, thereby optimizing the effectiveness of preventive measures (Obermeyer and Emanuel 2016).

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The emergence of artificial intelligence (AI) has spurred exponential growth in ML models outperforming current CVD prediction tools. A recent systematic review found AI models outperformed traditional risk calculators in the discrimination of atherosclerotic cardiovascular disease (ASCVD) risk (Liu et al. 2023). Other CVDs addressed by AI models include acute coronary syndrome (ACS), heart failure (HF), hypertension (HTN), and arrhythmia (Al-Zaiti et al. 2023; Quer et al. 2021).

While many models have been developed, few AI-based CDS have been adopted and evaluated in routine care; particularly in resource-constrained settings where careful allocation of resources is crucial to prioritize individuals at risk while minimizing overdiagnosis and harm for those not at risk (Albarqouni et al. 2022; Magrabi, Lyell, and Coiera 2023; Susanto et al. 2023). The progression from development to adoption of AI-based CDS is shaped by dynamic sociotechnical challenges, involving people, process, and environment which are critical for safe and effective adoption (Magrabi et al. 2019; Petersson et al. 2022).

Accordingly, we sought to explore the sociotechnical context of CVD risk assessment in resource-constrained settings and potential opportunities for AI-based CDS, focusing on (Ciecierski-Holmes et al. 2022; Wahl et al. 2018):

(1) How do doctors obtain information, use CDS, and make clinical decisions in resource-constrained settings?
(2) If given access to an AI-based CDS, which problems and clinical tasks would doctors prefer to have supported?

Of the nine dimensions of care delivery in resource-constrained settings, we specifically focused on ways AI-based CDS could address limited access to medical specialists and advanced equipment (van Zyl C et al. 2021). To the best of our knowledge, there is no previous work that understands the sociotechnical context of CVD prediction in resource-constrained settings (Magrabi, Cresswell, and Fraser 2023).

## Methods

### *Study context and setting*

Semi-structured interviews were conducted from August 2022 to February 2023. The study was undertaken in Indonesia, the world's fourth most populous nation with over 270 million people spread across 17,508 islands and 38 provinces (Wahyuni et al. 2023). Java is the most populous island, accounting for approximately 57% of the population. Indonesia faces significant health challenges, including the double burden of disease – the coexistence of infectious and non-communicable diseases such as CVD (2017). See Supplement 1 for details about the health, medical education, and payment systems.

Based on World Health Organization (WHO) guidelines of a doctor-to-population ratio of 1:1,000, Indonesia is currently understaffed with only 130,000 doctors serving, indicating a deficit of 140,000 additional doctors (Mahendradhata et al. 2017). Most doctors (57%) are located in Java. There are fewer than 1,500 cardiologists (1:180,000 cardiologist-to-population ratio) nationwide with most concentrated in urban areas, resulting in uneven access to cardiology services in remote areas (Qanitha et al. 2022).

### *Recruitment*

We sought to interview GPs working in primary care or class C or D hospitals; and cardiologists working at class B or C hospitals (see Supplement 1; Figure S1). In these low-resource settings, access to medical specialists or advanced equipment for confirmatory diagnosis is limited. The study invitation was emailed, and a snowballing strategy was subsequently used whereby participants recommended colleagues, for example, who work in other geographical units or health facilities. Purposive sampling was used to ensure representation across a spectrum of clinical contexts (Palinkas et al. 2015). The sample size was determined based on the exploratory design of the study, given the diverse geographical spread and variable availability of the resources. We continued interviews until reaching saturation (Braun and Clarke 2019). As data collection and analysis were conducted

iteratively, saturation was assessed through regular discussion among the research team and was considered reached when additional interviews no longer generated new codes or themes relevant to the research questions.

### *Data collection*

Investigators (APS and FM) developed open-ended guiding questions (Supplement 2; Table S1). The interview guide was pilot tested in July 2022 with a cardiologist (BW) for clinical relevance. The final interview question presented three potential use cases for AI-based CDS covering the major CVDs and asked participants to identify the most suitable one for their workplace (Figure 1). The use cases were informed by existing literature on ML prediction models for HF (Yao et al. 2021), atrial fibrillation (Yum et al. 2022)—the most prevalent type of treated heart arrhythmia (Chugh et al. 2001)—and ASCVD (Kakadiaris et al. 2018). They were selected because they represent major cardiovascular health challenges in Indonesia and can be assessed using basic clinical data, widely available laboratory tests, or other simple examinations such as ECG. To reflect the realities of resource-constrained settings, the models did not rely on advanced diagnostic technologies, such as treadmill testing, echocardiography, or CT scan.

Interviews were conducted online via Zoom to facilitate participation from diverse geographical areas and leverage the widespread adoption of video conferencing following the COVID-19 pandemic (Keen, Lomeli-Rodriguez, and Joffe 2022). Interviews were conducted in Bahasa Indonesia by a trained interviewer (APS), a GP with experience in remote practice, enabling participant to respond in their native language. Prior to the interviews, all participants provided informed consent, after which we collected doctors' baseline profiles (i.e. gender, age group, clinical role and experience (as GP or Cardiologist), work setting (hospital or primary care), as well as the reported setting of their workplace, whether urban or rural).

Interviews were audio-recorded and transcribed in Bahasa Indonesia by investigator APS. Subsequently, APS translated the transcripts into English, which were then reviewed by investigator BW. We used a literal translation and an iterative process for refinement. Any discrepancies identified during translation were cross-checked against the original transcripts and, if necessary, verified with participants (Fryer 2019; Regmi, Naidoo, and Pilkington 2010; Squires 2009).

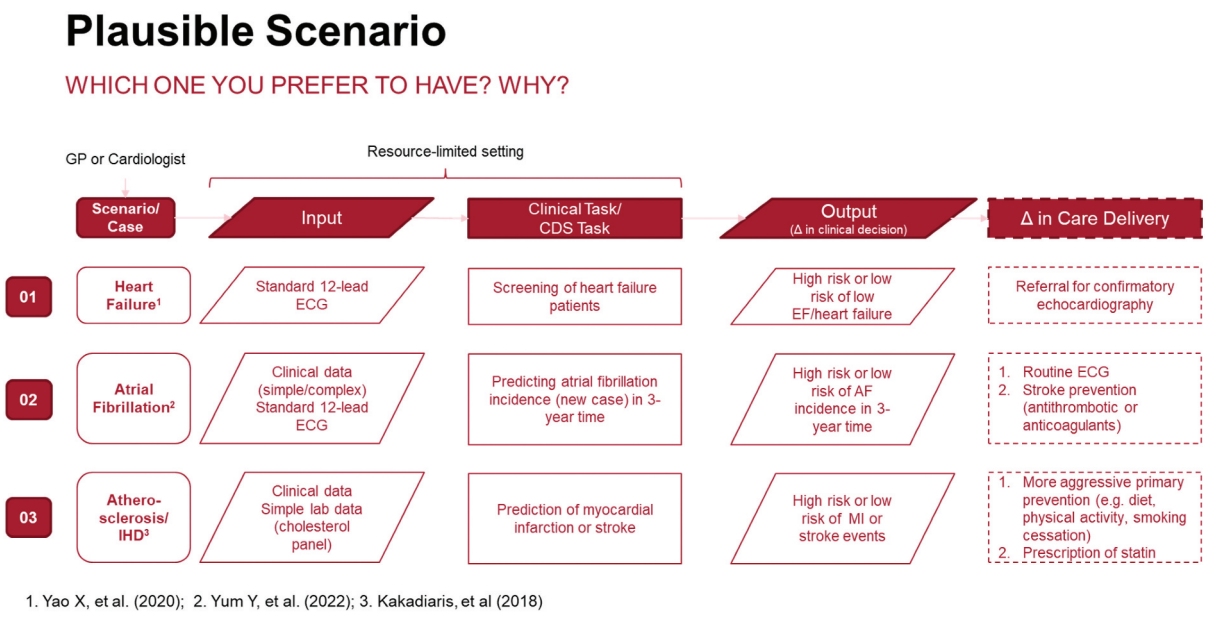



**Figure 1.** Three different scenarios on the use cases of AI-based CDS, which were drawn upon existing literature about ML prediction models for HF (Yao et al. 2021), AF (Yum et al. 2022), and ASCVD (Kakadiaris et al. 2018). Note: abbreviation: AF = atrial fibrillation, CDS = clinical decision support, ECG = electrocardiogram, EF = ejection fraction, GP = general practitioner, IHD = ischemic heart disease, MI = myocardial infarction, Δ = change.

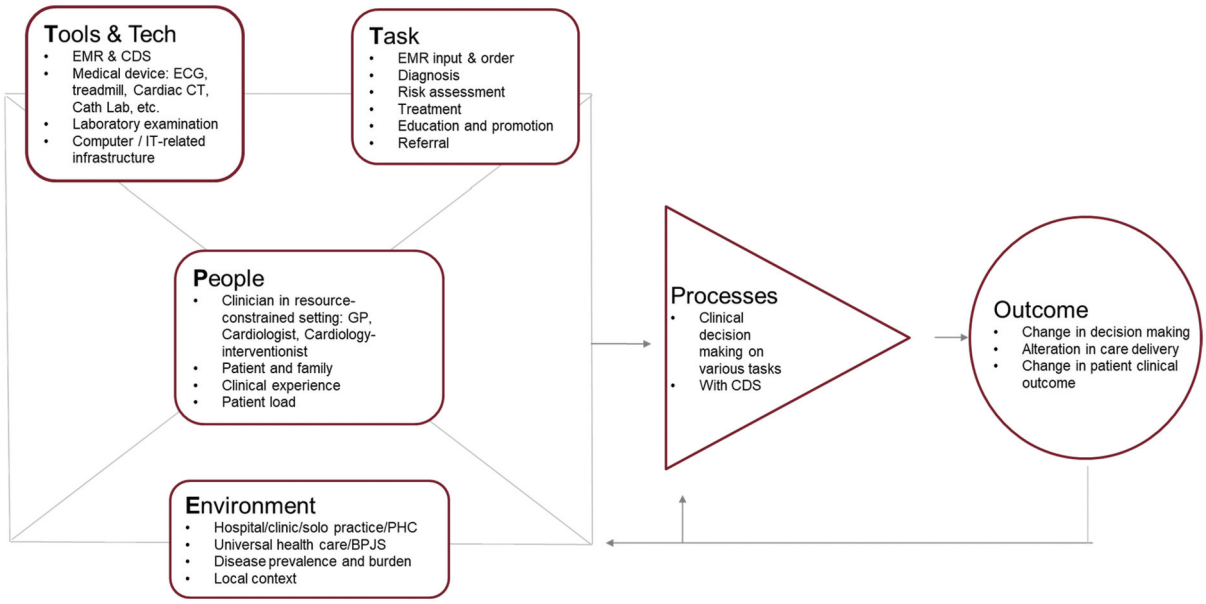



**Figure 2.** Coding based on PETT scan of the SEIPS 101 framework (Holden and Carayon 2021). Note: BPJS = *Badan Penyelenggara Jaminan Kesehatan (Social security agency providing universal health coverage)*, Cath Lab = catheterization laboratory, CDS = clinical decision support, CT = computed tomography, EMR = electronic medical record, GP = general practitioner.

### *Data analysis*

We analyzed the translated data iteratively using a six-step deductive thematic approach (Braun and Clarke 2006). Analyses were guided by the SEIPS (Systems Engineering Initiative for Patient Safety) theoretical framework, focusing on people, environments, tools, and tasks (PETT) (Carayon et al. 2006). The PETT scan serves as a tool primarily used to describe a complex sociotechnical system, particularly in categorizing data into factors (Holden and Carayon 2021). Initially, all translations were read to gain familiarity with the data, noting initial ideas. Subsequently, two investigators (APS and FM) synthesized the initial codebook based on the PETT scan of the SEIPS 101 framework (Figure 2). Using these codes, the entire translated dataset was coded by investigator APS with NVivo 12, a qualitative data analysis tool. Coded data were reviewed by another investigator (SA). Discrepancies were resolved through consensus in regular investigator meetings by returning to the relevant transcript excerpts, clarifying code definitions, and refining the PETT-based coding framework. Key quotes were highlighted from each transcript to provide operational evidence to support the themes. However, participants were not asked to provide feedback about the emerging themes. The findings were reported according to the Standards for Reporting Qualitative Research (SRQR; Supplement 3; Table S2) (O'brien et al. 2014).

### *Reflexivity*

The research team comprised clinicians (APS, BW, SA) and health informatics researchers (DL, SB, FM). APS and BW hold current medical licenses in Indonesia and previously worked in remote settings but had no professional involvement in participants' workplaces. DL, SB, and FM are based in a high-income country and had limited direct experience of healthcare delivery in resource-constrained settings. APS conducted the interviews and had no prior relationship with most participants; previous contact with three participants had occurred more than 10 years earlier and was not ongoing. APS de-identified all transcripts before sharing them with the research team.

## Results

We interviewed 27 doctors, including 16 GPs and 11 cardiologists (Table 1). The majority of participants ($n = 23$, 85%) were under 35 years of age, 16 identified as male (59%). Most practiced in urban areas and

**Table 1.** Baseline characteristics of interview participants ($n = 27$).

| | GP ($n = 16$) | Cardiologist ($n = 11$) | Total ($n = 27$) |
|---|---|---|---|
| *Gender* | | | |
| Male | 8 | 8 | 16 |
| Female | 8 | 3 | 11 |
| *Age group* | | | |
| <26 | 1 | | 1 |
| 26–30 | 7 | 2 | 9 |
| 31–35 | 4 | 9 | 13 |
| 36–40 | 3 | | 3 |
| 41–45 | 1 | | 1 |
| *Clinical experience* | | | |
| <3 years | 6 | 11 | 17 |
| 3–5 years | 7 | | 7 |
| >5 years | 3 | | 3 |
| *Self-reported setting* | | | |
| Urban | 13 | 8 | 21 |
| Rural | 3 | 3 | 6 |
| *Clinical setting* | | | |
| Hospital | 4 | 11 | 15 |
| Primary care | 12 | | 12 |
| *Geographical units* (ISO Online Browsing Platform 2023) | | | |
| Java | 11 | 4 | 15 |
| Kalimantan | | 1 | 1 |
| Maluku | 3 | 1 | 4 |
| Nusa Tenggara | | 1 | 1 |
| Papua | | 1 | 1 |
| Sulawesi | | 1 | 1 |
| Sumatera | 2 | 2 | 4 |

Note: GP = general practitioner.

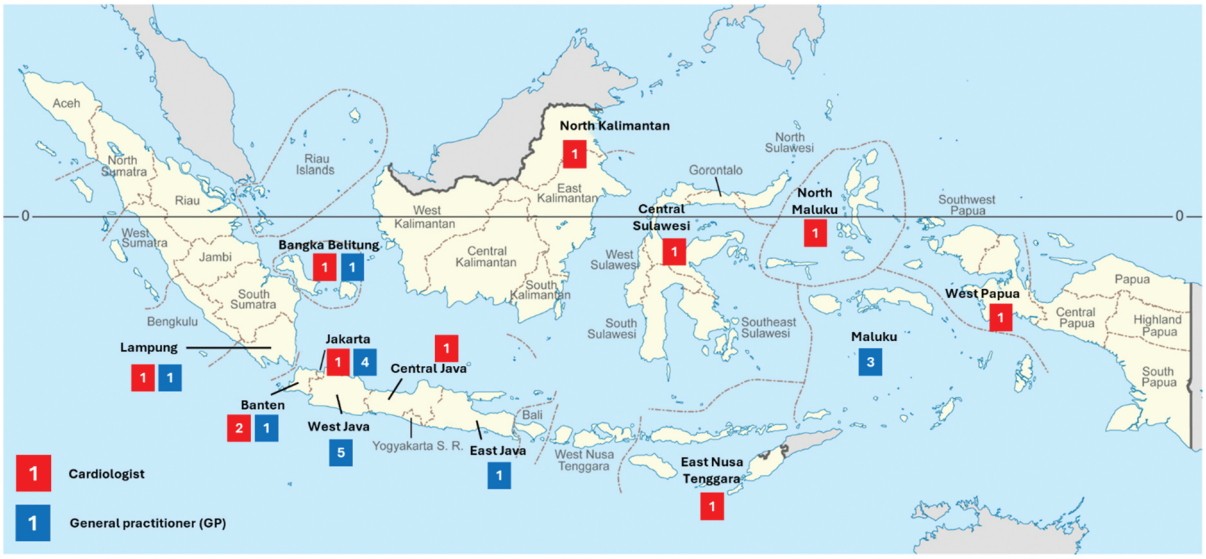



**Figure 3.** Distribution of interview participants across all the geographical units of the Indonesian archipelago. Map was adapted from Wikipedia by overlaying the number of interviewees per province under CC BY-SA 3.0 2024.

were distributed across 13 provinces covering all 7 geographical units of the Indonesian archipelago (Figure 3). The median duration of the interview was 23 minutes (IQR 19.5–28.5).

Our examination of the sociotechnical context of CVD risk prediction revealed five themes which are described in the following sections (Table 2). Selected quotes from each theme are presented in Box 1.

### *Theme 1: high patient load contributes to suboptimal care delivery*

Participants reported seeing 30 to 100 patients per day, and this patient load limited the time to conduct thorough clinical assessments. The use of paper records resulted in numerous repetitive tasks, such as

**Table 2.** Deductive themes to describe the sociotechnical context of CVD risk prediction in Indonesia based on the PETT scan of the SEIPS framework, themes specific to ASCVD, ACS, HTN, and HF are highlighted (Carayon et al. 2006; Holden and Carayon 2021).

| THEME | People | Environment | Tools | Tasks |
|---|---|---|---|---|
| (1) High patient load contributes to sub-optimal care delivery. | • Doctors see 30–100 patients per day.<br>• Inadequate access to cardiologists in many cities and provinces. | • The UHC system mandates that chronic patients visit a doctor every 1–2 weeks for medication prescription. | • Existing systems do not support quick patient assessment and follow-up of chronically ill patients.<br>• Current tools do not support automated acquisition of input data for CDS. | • Insufficient time for objective risk and scoring.<br>• Repetitive tasks, such as prescription for chronic patients<br>• No time to verify medication type and dosage for repeat prescriptions. |
| (1) Decision-making is largely subjective, based on clinical experience and consultation with colleagues. | • Doctors estimate risks subjectively based on experience.<br>• Doctors recognize the potential of AI-based CDS. | • UHC payment is based on diagnosis codes, therefore comprehensive investigation and treatment is not supported. | • Doctors communicate and discuss patient cases through mobile messaging platforms, such as WhatsApp Groups. | • Doctors recognize that risk assessment and scoring is fundamental to patient management. |
| (1) Clinical guidelines for major CVDs (ACS, HF, HTN) are difficult to implement. | • **ACS**: Inadequate access to cardiology interventionists for PCI.<br>• **HTN**: Low patient compliance/ adherence to medication or follow-up. | • **ACS**: Patients must travel to get treatment, long duration, and difficult mode of transport. Patients and family consider cost of transportation and living at destination. | • **ACS & HF**: Limited laboratory examination and imaging, such as cardiac enzyme, catheterization and echocardiography.<br>• **ACS & HF**: No tools to communicate with secondary or tertiary facilities about the availability of investigations. | • **ACS**: Risks are estimated subjectively and explained to patient/family.<br>• Referral is usually achieved by consensus between doctor and patient/ family. |
| (1) EMR and CDS use is limited. | • Doctors lack experience or have very limited exposure to EMR. | • Current use of EMR is for coding and driven by UHC.<br>• EMR also used for administrative purposes e.g. to track waiting time in clinics. | • At most sites, computers are generally available at doctor desk.<br>• **EMR** availability varied, with some transitioning from paper.<br>• **CDS** generally used on mobile devices and not embedded in the EMR. | • Duplication of medical record entries (paper and electronic) during transition period.<br>• CDS is used for evidence retrieval.<br>• Data input to CDS is manual. |
| (1) Risk prediction of **ASCVD** is the most preferable use case for AI-based CDS. | • Poor patient compliance and adherence to follow-up, especially those with risk factors. | • **ACS**: High burden in the area due to unhealthy local lifestyle. | • Cholesterol panels are widely accessible. | • Education on primary prevention is crucial.<br>• Different levels of statin prescription are possible.<br>• Risk assessment is required to differentiate and manage high-risk patients. |

Note: ACS = acute coronary syndrome, AI = artificial intelligence, ASCVD = atherosclerotic cardiovascular disease, CDS = clinical decision support, EMR = electronic medical record, HF = heart failure, HTN = hypertension, PCI = percutaneous coronary intervention, UHC = universal health coverage.

prescribing medications for chronic patients; and there was no time to recheck the type and dosage of prescribed medications. The UHC scheme limited the amount and value of CVD medications that could be prescribed at each visit which meant doctors needed to ration medications based on the monetary value as well as the number of medications allowed. For instance, chronically ill patients needed prescriptions to be re-filled every 1 to 2 weeks.

Many doctors reported using various CDS during their training or at the onset of placements, particularly when patient volumes were lower. As the patient queue grew, they tended to deprioritize CDS use and

**Box 1.** Selected quotes from each theme describing the sociotechnical context of CVD risk prediction.

**Theme 1: High patient load contributes to suboptimal care delivery.**

*". . . because there are large number of patients, we need an efficient way to serve patients. [. . .] Because in Indonesia, number of doctor and patients is not proportional, like in Puskesmas, one doctor can provide 50 to 100 patients in 3 hours [. . .] GP handles so large number of patients."* – ***Doctor 25***

*"Honestly, I have used many other (CDS) tools, but only in the beginning . . . but . . . because I had too many patients, I just followed along . . . Honestly, when I'm tired, I already have 20 patients in the morning, and then more in the afternoon, and then back to practice in the evening, . . . Because I have a lot of patients, sometimes I don't have time to look or check my phone again for that (CDS)."* – **Doctor 13**

**Theme 2: Decision-making is largely subjective, based on clinical experience and consultation with colleagues.**

*"Rarely (using CDS or tools to make decisions), just based on my experience."* – **Doctor 17**

*"Additionally, the limitation of resources is a challenge . . . Theoretically, we can refer to guidelines . . . or else share patient cases in a (WhatsApp) group. If we don't understand something and need a quick answer, we can ask in this group."* – **Doctor 13**

**Theme 3: Clinical guidelines for major CVDs (ACS, HF, HTN) are difficult to implement.**

*"For primary PCI, it's not available here and it's far away, around 7 hours from here . . . If we do primary PCI there, it can worsen the patient's condition during transportation. [. . .] As for cardiac enzymes, sometimes we have them, and sometimes we don't, so we must keep evaluating the laboratory and updating supplies. [. . .] For NT Pro-BNP (for HF), we still send it to [province's capital city], so currently we don't have NT Pro-BNP available here"*

– **Doctor 06**

*" . . . .there was no cardiologist in one district, and it took 12–24 hours to access the nearest specialist. So it is indeed very difficult for us, especially when we are constrained by supporting equipment such as ECG machines that are starting to malfunction, and there are no lab facilities to aid in the diagnosis using cardiac enzymes, etc."*

– **Doctor 09**

**Theme 4: EMR and CDS use is limited.**

*"We still use paper medical records, written by hand, not on a computer. [. . .] There is no computer in the cardiology clinic. There is only one computer for registration purposes at the clinic. [. . .] But if the patient's data is registered at the UHC front desk and then directed to the clinic, the record-keeping at the clinic is still using paper [. . .] It's hard to take a patient's medical history when they come to the emergency department . . . we usually must wait until the next morning to access their (paper) medical records."* – **Doctor 05**

**Theme 5: Risk prediction of ASCVD is the most preferable use case for AI-based CDS.**

*"I prefer number 3 (AI-based CDS ASCVD risk prediction), because its utility is clear [. . .] In my opinion, this is a good material to use for patient education. Sometimes when we see a patient who smokes and has high cholesterol, we just say 'oh, this patient is at risk for heart disease,' but we don't describe it in detail. If we have an objective picture that can be shown to the patient, that would be great. . . . . but since it's based on a calculator, we must type it in ourselves, and we don't have enough time to do that. If this tool is used, it is very useful and relevant from input to output to care delivery, whether the patient needs a statin and what intensity of statin they need based on their basic values, such as LDL."* – **Doctor 15**

Note: ACS = acute coronary syndrome, AI = artificial intelligence, ASCVD = atherosclerotic cardiovascular disease, CDS = clinical decision support, EMR = electronic medical record, GP = general practitioner, HF = heart failure, HTN = hypertension, LDL = low density lipoprotein, NT pro-BNP = N-terminal pro b-type natriuretic peptide, PCI = percutaneous coronary intervention, UHC = universal health coverage.

relied more on their subjective clinical judgment to make decisions swiftly. Doctors favored CDS capable of rapidly assessing and prioritizing high-risk patients. They also expressed a preference for automated data acquisition over manual input, given the substantial patient load they managed daily. For example, doctors noted the utility of a CDS pre-filled by patients or nurses that could facilitate automated risk assessment or differential diagnosis before patient consultations. Such a tool would allow them to devote more attention to high-risk patients, streamline discussions to key points, and conduct more comprehensive assessments during consultations.

### *Theme 2: decision-making is largely subjective, based on clinical experience and consultation with colleagues*

Doctors described the limited availability of supporting investigations, including electrocardiogram (ECG), complex laboratory, and imaging procedures. As such, decisions were based on history taking, physical examination, and clinical experience. When laboratory investigations were accessible, ordering depended upon the UHC claim structure, which was organized according to case-based groups rather than specific investigations. For example, cardiac enzyme tests, crucial for distinguishing between two types of ACS, namely non-ST-elevation myocardial infarction and unstable angina pectoris, might not be conducted due to their classification under the same case-based group claim in the UHC system.

Nevertheless, doctors emphasized the need for more objective tools to aid decision-making, particularly in cardiology where risk assessment and scoring is fundamental to patient management. For instance, doctors cited the GRACE score which predicts the risk of adverse events following ACS (see Box 2 for other examples).

In times of uncertainty, advice was sought from colleagues, primarily through mobile messaging platforms like WhatsApp groups. For instance, cardiologists reported sharing photos of ECGs with a group of

**Box 2.** Tasks for which doctors used CDS.

- Calculate dose of medicine or IV fluid, especially for pediatrics.
- Risk prediction or scoring, e.g. ASCVD calculator, GRACE, TIMI, HAS-BLED, $CHA_2DS_2$-VASc, SOFA, Lee Revised, Mehran score, etc.
- Diagnostic criteria, e.g. Killip, Wells, ISTH, rheumatic heart disease, appendicitis, etc.
- Clinical calculator, e.g. BMI, GFR, Bazett QT interval, etc.
- Imaging and interpretation, e.g. diastolic dysfunction calculator for echocardiography.
- Evidence retrieval for difficult or rare cases (e.g. QxMD, MDcalc, UpToDate, Medscape, Google).

Note: ASCVD = atherosclerotic cardiovascular disease, BMI = body mass index, $CHA_2DS_2$-VASc = score for atrial fibrillation stroke risk, GFR = glomerular filtration rate, GRACE = global registry of acute coronary events, HAS-BLED = score for major bleeding risk, ISTH = International Society on Thrombosis and Hemostasis, IV = intravenous, SOFA = sequential organ failure assessment, TIMI = thrombolysis in myocardial infarction.

fellow cardiologists to quickly obtain a second opinion. In one case, a small-town GP in West Java maintained a local doctor group, including a cardiologist.

### *Theme 3: clinical guidelines for major CVDs (ACS, HF, HTN) were difficult to implement*

Doctors reported several barriers to clinical guideline implementation. The availability of cardiologists was a major barrier, with some areas only having one cardiologist for an entire city or province. Cardiology interventionist sub-specialists were also rare, this meant that immediate primary percutaneous coronary intervention (PCI) for myocardial infarction was not possible in many areas and patients needing this procedure had to be referred to other facilities.

However, the available modes of transportation and time to reach referral facilities made it practically impossible to meet the specified time-to-treatment guidelines. In the Eastern Indonesian islands, for instance, travel to a PCI facility involved an overnight journey by sea or a 30-min flight available only three-times a week. Given transportation barriers, doctors sought effective communication tools to liaise with higher-level facilities regarding the availability of necessary resources, consultation opportunities, and feedback mechanisms to facilitate informed referral decisions.

When the possibility of referrals arose, patients and their families considered various socio-economic factors. While medical expenses were covered by the UHC, the costs associated with transportation and accommodation at the referral destination were significant concerns. Patients and families thus preferred treatment in their hometown despite limitations in local facilities. Consequently, referrals were frequently delayed by negotiations with patients, families, and other doctors.

In making referral decisions, most doctors relied on subjective risk estimation and offered general health promotion or education to patients and families. This reliance prompted a preference for CDS tools to objectively assess risk. Risk prediction CDS were also seen as an effective way to inform and educate patients and families, with the results serving as reminders. Patients and families were often aware of the severity of the condition but were hesitant to seek ideal treatment through referral.

### *Theme 4: EMR and CDS use is limited*

Computers were typically accessible at doctors' desk, although exceptions existed at certain sites. Where available, doctors expressed concerns regarding the speed and reliability of the network for operating information systems such as EMR or CDS, aiming to avoid any delays in clinical work.

Doctors described various purposes for using computers. Most patient administration and claims were processed electronically, driven by UHC claim requirements. Hospital and clinic management saw EMRs as tools for administrative tasks and monitoring service quality, such as measuring patient waiting times, rather than as clinical aids.

EMR availability varied, spanning from paper records to comprehensive systems. Many doctors had very limited or no EMR experience. Some were in a transitional phase from paper to electronic records, necessitating duplicate data entry. When EMRs were accessible, their scope was often limited compared to the primary documentation maintained on paper. For instance, at certain sites, EMRs were solely used for outpatient clinics, with inpatient wards still on paper. The continued use of paper records posed challenges in clinical tasks, such as providing timely and comprehensive care in emergency departments due to missing or delayed access to past records outside regular hours.

EMRs primarily served as digital repositories of patient information and were seldom integrated with CDS. Nearly all participants reported prior experience with CDS tools. Doctors commonly utilized CDS, often relying on personal devices such as mobile phones or tablets to manually input necessary variables. Popular applications included those for evidence search, pediatric dose calculations, risk scoring, and clinical calculators (Box 2). Doctors recognized the significance of risk scoring, particularly in cardiovascular medicine.

### *Theme 5: risk prediction of ASCVD is the most preferable use case for AI-based CDS*

The majority of doctors (17 of 27; 63%) opted for ASCVD risk prediction as the most feasible among the three presented options, reflecting the availability of required inputs and the actionability of the resulting recommendations. Common reasons included the high prevalence of ACS, the proactive nature of risk prediction facilitating lifestyle education, and the increased awareness and accessibility to cholesterol panels.

Both GPs and cardiologists unanimously recognized ACS, primarily stemming from atherosclerosis, as a significant burden throughout Indonesia, thus emphasizing the importance of early intervention. However, many patients presented late in the disease course, highlighting a pressing need to reduce prevalence. This consideration was noted to be particularly crucial given the challenges with referrals and resource gaps in managing coronary artery diseases, including the availability of stress tests, CT angiograms, and cardiac catheterization laboratories.

Doctors noted that risk prediction had the potential to serve as an objective discussion point to promote lifestyle changes among patients. In resource-constrained settings, where comprehensive examinations are lacking, AI-based predictions could facilitate explaining conditions objectively to patients. Furthermore, higher risk predictions could incentivize patients to pursue more aggressive treatments, including referrals. For cardiologists, risk assessment could help overcome GPs' hesitancy to refer high-risk patients who require specialized attention. Cholesterol-reducing medications were widely accessible, and doctors stressed the importance of differentiating between moderate- and high-intensity statins based on risk stratification.

## Discussion

Despite the enthusiasm surrounding model development, the application of AI to support clinical decision-making in resource-constrained clinical settings is understudied (Magrabi, Lyell, and Coiera 2023; Susanto et al. 2023). We conducted interviews guided by the SEIPS framework to better understand the socio-technical context of managing CVDs and discussed possible use cases for AI-based CDS.

Our results confirm that doctors were overwhelmed by the patient volume; medical records were mostly maintained on paper; and clinical decisions were largely based on subjective experience due to poor access to confirmatory examinations. As such, risk prediction is needed to prioritize and educate high-risk patients. Doctors agreed that ACS resulting from atherosclerosis was the most prevalent CVD problem in the health system and emphasized the crucial role of primary prevention in alleviating the disease burden. There is, thus, untapped potential for utilizing AI to improve risk prediction as part of primary prevention strategies for ASCVDs in the Indonesian context.

### *Problem-driven approach for AI-based CDS*

We demonstrate an approach for qualitatively assessing real-world challenges in clinical decision-making amid the constraints of combating a prevalent disease. This approach diverges from the prevalent data-centric and technology-driven methods typically observed in high-resource settings, instead emphasizing the development of CDS tailored for resource-constrained environments (Magrabi, Cresswell, and Fraser 2023). Given the diverse resources, challenges, and priorities across different health systems and local contexts within the realm of global health, it is imperative to adopt a user-centered approach to CDS development. This approach, aligned with contemporary best practices, ensures a thorough understanding of user needs, thereby mitigating issues such as increased workload as well as poor integration with clinical workflow and usability (Brunner et al. 2017;

Sanderson et al. 2023). By addressing the intricate sociotechnical challenges inherent in healthcare systems, the effective integration of AI-based CDS can maximize benefits and minimize risks (Magrabi et al. 2019; Salwei and Carayon 2022).

Doctors described ASCVD as a prominent health concern in Indonesia, exerting a significant impact across various demographic and socioeconomic strata (Adisasmito et al. 2020; Uli et al. 2020). Given the complex challenges associated with providing timely curative interventions for myocardial infarction, prioritizing the prevention of atherosclerosis becomes imperative (Heine and Hanekom 2023). In this regard, AI presents an opportunity to implement cost-effective preventive medicine programs by accurately predicting individual risk profiles (Ciecierski-Holmes et al. 2022). AI tools can support better risk prediction, i.e. enabling referral only of the high-risk patients to specialists for further investigation. Therefore, AI can ensure effective use of the existing resources, i.e. specialists and equipment. While a clinical guideline-based risk assessment CDS tool exists for primary ASCVD prevention (Lloyd-Jones et al. 2019), it is important to note that this rule-based CDS was primarily developed using data from cohorts of other ethnicities and predominantly addresses conventional risk factors. Given ethnicity-specific prediction models are rapidly emerging (Sibarani et al. 2022), the current study takes a problem-based approach to specifically examine the broader sociotechnical context of CVD prediction. The preference of ASCVD risk assessment may reflect its perceived feasibility, clinical relevance, and familiarity in routine clinical practice, rather than it was considered the highest-priority application.

While AI-based tools are increasingly being used for risk assessment (Susanto et al. 2023), they pose a significant challenge for doctors in resource-constrained settings, where access to comprehensive laboratory or imaging examinations may be limited. Despite this challenge, risk assessment plays a crucial role in facilitating efficient allocation of limited resources, such as avoiding unnecessary medications (e.g., statins or aspirin) for patients deemed to be at low risk (Modesti et al. 2014). Conversely, for patients identified as high risk, targeting controllable risk factors becomes paramount, with the aim of achieving absolute risk reduction (Gold et al. 2022). For AI to be adopted, it should develop clinically comprehensible outputs through explanation (e.g., risk factors or feature attribution) over "black-box" predictions, would need to be trusted by the user and providing explanations for blackbox AI outputs is a critical factor in achieving this doctors' trust (Diprose et al. 2020).

In addition, to be effective AI recommendations must extend beyond clinical decision-making to encompass the accessibility of subsequent care delivery (Alami et al. 2020). For instance, in the context of ASCVD risk stratification, the decision regarding statin prescription relies heavily on the accuracy of risk assessment. AI-based systems can effectively address the uncertainty surrounding statin prescription, as highlighted in previous qualitative study conducted among Indonesian healthcare providers (Irawati et al. 2020). Our study corroborates these findings, indicating that clinical experience predominantly influences subjective decision-making and prescription practices in resource-constrained settings.

To that end, AI design in resource-constrained settings should prioritize actionability and sustainability of the care recommendation, ensuring that it does not exacerbate existing system pressures or introduce new ethical concerns (A. P. Susanto et al. 2026). During implementation, AI tools should be guided by clinical consensus and local policies, with ethical oversight ensuring transparency and accountability. This supports practical use while reducing unintended consequences to care delivery.

### *Automated CDS on mobile devices*

In addressing the challenge of manual data entry due to heavy patient loads, doctors emphasized the need for automation. In high-resource settings, this automation is often achieved by integrating CDS directly into the EMR, ensuring seamless data input through interoperable resources (Abedin et al. 2020). However, in resource-constrained settings, limited EMR availability means that AI-based tools may need to function in paper-based or sparse-data settings. This has important design implications. Systems should support low-burden manual data entry, staged completion of missing information, and clear signaling when insufficient data reduce the reliability of AI recommendations (Westerbeek et al. 2022). Notably, our study revealed that the majority of CDS tool usage occurred on mobile devices. These findings align with previous research, which found a preference for mobile-based CDS for CVD management, with non-physician healthcare workers responsible for data input (Praveen et al. 2014;

Vedanthan et al. 2015). While participants acknowledged the potential role of nurses in such data collection, none of them suggested that doctors could be replaced by nurses who were assisted by an AI tool.

Mobile devices were frequently utilized for communication and consultation with colleagues regarding clinical cases, with WhatsApp emerging as a popular platform. This finding is also consistent with previous studies highlighting the utility of WhatsApp for remote consultation, particularly in resource-constrained environments (Gulacti et al. 2016; Weaver et al. 2022). However, concerns persist about mechanisms for record-keeping and privacy on WhatsApp, which remain unclear (Morris, Scott, and Mars 2021).

### *Strengths and limitations*

This study adds to the growing body of knowledge about applying AI for medically underserved populations in resource-constrained settings (Fraser et al. 2023; Wahl et al. 2018). We focused on doctors with limited access to specialists and advanced examinations, which are two main challenges for CVD management (van Zyl C et al. 2021). Our findings about the use case for AI to support risk assessment for ASCVD may, therefore, be applicable to settings facing similar challenges in access to specialist support and advanced medical equipment.

The interview transcripts were translated by APS, who led this study and is a native Bahasa Indonesia speaker with a tertiary education from an English-speaking country. His deep understanding of both languages, clinical terminology, and the socio-cultural context ensured an accurate capture of participants' meaning and intent (Fryer 2019; Squires 2009). While certified translators were not available for this study and back-translation was not undertaken, bias in data analysis was mitigated by several steps: an initial codebook was developed collaboratively with FM, translations were reviewed by BW, coded data was evaluated by SA, and reflexivity notes maintained by APS documenting interview impressions, translation decisions, coding developments, and emerging interpretations throughout the study. Regular investigator meetings facilitated discussion of findings, resolution of discrepancies, and finalization of themes. This study relied solely on interview data; future research could benefit from incorporating observations or other ethnographic methods to gather additional rich and contextual insights. Most of our participants came from Java representing the actual population distribution and were early-career doctors who make up a significant proportion of the workforce as they are required to gain clinical experience in resource-constrained settings as part of their training (Putri et al. 2021). While sampling was purposive covering all seven geographical units in Indonesia and data saturation was achieved, the findings may not be transferable all areas due to variations in provincial policies, particularly regions that have autonomy in health (Kristiansen and Santoso 2006). Additionally, some participants faced challenges in providing insights due to limited familiarity with CDS and AI, particularly those with minimal exposure to informatics. Our methodology was designed to address this issue firstly by asking participants an open-ended question about AI-based CDS and explaining the concept (see Supplement 2; Table S1). We then presented three potential use cases for AI-based CDS covering the major CVDs and asked participants to identify the most suitable one for their workplace.

It is also important to note that EMRs were previously not regulated in Indonesia. However, during the interview period, the Ministry of Health issued a new regulation on EMRs dated August 31, 2022 (Hakam et al. 2023). Although this regulation is not expected to immediately shift practices from paper records to EMR and such a transition may take years, there was a potential for participant bias influenced by social acceptability, particularly considering the media attention surrounding the Ministry's transformation program.

## Conclusions

Introduction of AI-based CDS should be driven by clinical needs and must account for the sociotechnical context. Risk assessment for ASCVD represents a compelling use case for AI-based CDS to improve primary prevention and reduce disease burden in the Indonesian context. Further studies are required to investigate its potential impact on decision-making and clinical management.

## Abbreviations

| | |
|---|---|
| ACS | Acute coronary syndrome |
| AI | Artificial intelligence |
| ASCVD | Atherosclerotic cardiovascular disease |
| CDS | Clinical decision support |
| EMR | Electronic medical record |
| GP | General practitioner |
| HF | Heart failure |
| HTN | Hypertension |
| PCI | Percutaneous coronary intervention |
| UHC | Universal health coverage |

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## Author contributions

CRediT: **Anindya Pradipta Susanto:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Investigation, Methodology, Project administration, Resources, Software, Supervision, Validation, Visualization, Writing – original draft, Writing – review & editing; **David Lyell:** Supervision, Writing – review & editing; **Saba Akbar:** Formal analysis, Investigation, Validation, Writing – review & editing; **Bambang Widyantoro:** Data curation, Formal analysis, Investigation, Resources, Writing – review & editing; **Shlomo Berkovsky:** Supervision, Writing – review & editing; **Farah Magrabi:** Conceptualization, Funding acquisition, Methodology, Supervision, Writing – review & editing.

## Disclosure statement

No potential conflict of interest was reported by the authors.

We utilized Generative AI (ChatGPT-3.5 by OpenAI) in the writing process, i.e. to paraphrase and refine parts of the final text to improve clarity and overall readability in February–March 2024. All output was meticulously checked, and the authors take responsibility for the final text.

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## Data availability statement

All data relevant to the analysis are included in the article and online supplementary material. The complete datasets generated and analyzed during the current study are not publicly available because consent was obtained from participating doctors to the use of the interview for aggregate reporting only as a measure to protect their identity and confidentiality. All audio-recordings, transcriptions, and translations were archived on Macquarie University approved online platform and available from the corresponding author (anindya.susanto@ui.ac.id) on reasonable request subject to approval from the ethics committees.

## Ethics approval and consent to participate

This study obtained ethical approval from Macquarie University Human Research Ethics Committee (Reference No: 520,221,032,837,485, Project ID: 10,328) and Faculty of Medicine Universitas Indonesia Ethics Committee (KET-586/UN2.F1/ETIK/PPM.00.02/2022). All participants provided written informed consent prior to data collection.

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