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Commentary

Combating cardiovascular disease disparities: The potential role of artificial intelligence

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1. Introduction

Artificial Intelligence (AI) is part of data science, utilizing computers to perform tasks requiring objective reasoning. Moreover, AI can analyze large health datasets (big data) from sources such as electronic medical records, imaging, insurance, smartphones, wearables, and genomics, reducing the cognitive burden of data interpretation [1,2]. Recent advances in AI in cardiovascular (CV) medicine support personalized preventive, diagnostic, and treatment approaches, termed precision medicine [3,4]. Additionally, AI has the potential to reduce CV health disparities via more precise and comprehensive risk analysis compared to existing general population models, integrating a broader range of CV risk factors, including genetic, behavioral, socioeconomic and environmental data [5–7]. While this review focuses on the US population, cardiovascular disease (CVD) is a global health issue, disproportionately impacting certain subpopulations internationally. For instance, a recent scoping review of AI for accurate disease diagnosis and CVD risk assessment included academic investigators from India, Serbia, Greece, Cyprus, Italy, Canada, UK and the US, highlighting global CVD challenges [8].

In the US, the racial and ethnic CV disparities are largely determined by social determinants of health (SDOH), including age, socioeconomic status, housing, transportation, education, healthcare access, along with structural racism, implicit bias, and mistrust in the healthcare system [9–11]. These disparities were further exacerbated during the COVID-19 pandemic, as US Black/African American, Hispanic, and Asian populations had a 20 % relative increase in CV mortality compared to White counterparts [12,13]. Although AI appears potentially transformative, it is not a panacea. Addressing persistent racial and ethnic disparities must include evidence-based medicine, equitable access and policies supporting healthy food options, adequate transportation, and increasing positive behavioral changes: physical activity, blood pressure (BP) monitoring and maintaining healthy body weight [14,15]. Finally, this commentary explores how AI may identify undetected societal and health patterns, enhance existing risk tools, and support efforts to reduce CV disparities.

1.1. AI and risk prediction

The uniqueness of AI lies in machine learning (ML), its ability to adapt and continuously learn from new data [16,17]. Thereby, AI-integrated risk prediction models can evolve and learn from diverse datasets, accurately representing populations and equitable across racial and ethnic groups [18]. This feature of ongoing data analysis improvement may address risk prediction bias, even in the most advanced traditional calculators, for certain minoritized groups, potentially avoiding over or underestimation [19,20]. An emerging advanced risk prediction model that could benefit from AI integration is the American

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Heart Association's Predicting Risk of cardiovascular disease EVENTs (PREVENT™) calculator, which employs multivariable models to predict developing CVD, atherosclerotic CVD and heart failure. This excellent tool exemplifies advanced data-driven approaches, from over 6 million diverse patients, to enhance CVD risk assessment, while addressing SDOH [21,22]. Predictors include sex, age, lipid levels, blood pressure (BP), body mass index, estimated glomerular filtration rate, diabetic status, smoking history, urine albumin-creatinine ratio, hemoglobin A1C and social deprivation index (SDI) [21–23]. Race, not a biological, but rather a social construct, was intentionally excluded, emphasizing that lived experiences and SDOH, rather than race itself, are primary drivers of observed racial CVD disparities, as corroborated by other researchers [11,20,24]. Accordingly, PREVENT accounts for racial and ethnic variations through SDOH, using SDI to measure area-based deprivation, integrating demographic characteristics and five-digit zip codes [21,22].

Potentially, AI can use risk calculators, such as PREVENT, as a foundational data point to integrate additional unaccounted factors to enhance accuracy and equity in CVD risk prediction, incorporating often overlooked factors, such as medications, including polypharmacy, co-existing medical conditions, family history, and genomics (Fig. 1). Moreover, AI may augment PREVENT predictive accuracy, tailoring it to local populations. In a recent cohort study of 38,147 patients across different racial and ethnic backgrounds, the ML-augmented PREVENT tool improved its calibration for Asian, White and Black/African American individuals, and reclassified approximately 11.5 % into different risk categories [25]. Further research is crucial to validate, establish reliability and applicability of ML-augmented risk calculations. Beyond refining individual risk prediction, ML may uniquely incorporate evolving SDOH factors that significantly impact CV health. For example, while the PREVENT SDI five-digit zip codes are static, providing only a cross-sectional snapshot, ML can analyze neighborhood trends, incorporating data from other sources, such as the US Postal Service, Housing Choice Voucher program, US Census American Community Service, commercial real estate, Google maps and marketing analytics [26]. These data sources could enable ML to predict neighborhood socioeconomic trajectories in real-time, identifying areas at increased risk due to declining resources or environmental factors, or conversely, those experiencing improvements. Correspondingly, a recent publication suggested that ML could be a beneficial tool for assessing the impact of urban gentrification, further refining PREVENT's five-digit zip code SDOH analysis [27]. By continually synthesizing and interpreting data from various sources, AI may overcome the limitations of static risk prediction tools, ultimately reducing CVD disparities and improving personalized prevention strategies for diverse populations. Conceivably, targeted public health policies and programs may mitigate the displacement of marginalized communities ahead of time and provide the necessary resources to improve SDOH.

1.2. AI in early recognition and management of CVD: a way to mitigate disparities

Early identification and appropriate control of CVD risk factors may best mitigate unfortunate and persistent disparities in CVD morbidity and mortality [15]. Therefore, AI could become a valuable asset, enabling real-time health monitoring, integrating technologies, such as smartwatches and biosensors, assessing BP, blood glucose, electrocardiograms (ECG), sleep cycle, and physical activity [28]. A key indicator of CV health, BP, may potentially be estimated using cuffless BP technologies with ML algorithms and physiological signals, including pulse wave analysis (PWA) and photoplethysmography (PPG). While PWA estimates BP by analyzing arterial pulse waves, PPG is an optical technique, measuring reflected or transmitted light to track changes in blood volume [29]. Cuffless BP technologies may be worn as wristwatches, potentially seamlessly tracking and recording vital data. However, PPG validity and accuracy may be less reliable with darker skin tones, as increased melanin absorbs more light, reducing signal quality [30,31]. Nevertheless, ongoing research aims to validate these technologies in diverse clinical settings, including cohorts with varying skin tones [31, 32]. Additionally, ML algorithms can refine BP estimation, mitigating skin tone biases, by identifying complex PPG signal patterns. Similarly, AI can improve the accuracy and quality of cardiac activity monitoring, interpreting heart sounds and ECG with greater accuracy than trained medical professionals [33,34]. For instance, AI-powered ECG

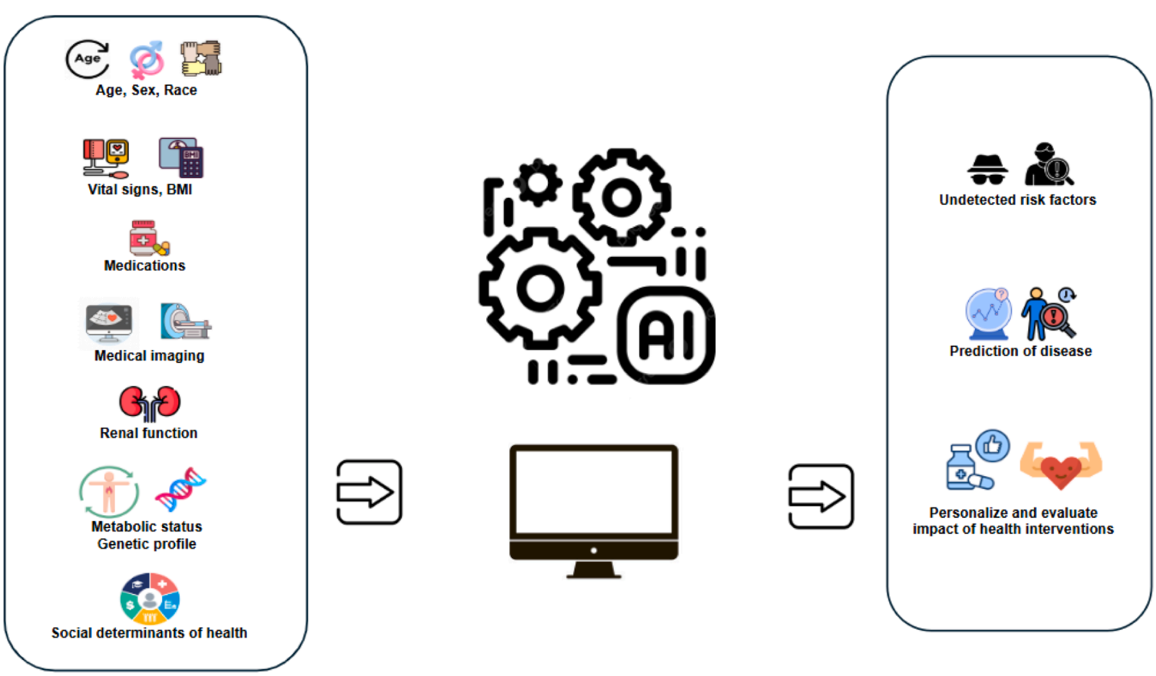


Fig. 1. Schematic showing AI processing of large datasets. AI can analyze large health datasets, identifying seemingly undetectable societal and health patterns, personalizing health interventions, and evaluating the impact of interventions, ultimately empowering clinicians and informing health policy decisions. Figure created by Orakwue, C. Et al.

technologies may detect hidden CVD up to 2 years earlier than traditional testing methods, including in diverse populations [33,35]. Therefore, AI has the potential to capture and analyze data from wearables, and if abnormalities are detected, notify patients, primary care clinicians, or emergency departments. Certain AI-powered wearables could also integrate geospatial technology to guide patients to the nearest healthcare facilities, provide public transportation schedules, and connect patients to non-emergency medical transport services. Hence, wearables, a rich source for data stream, when analyzed by ML algorithms, may identify potential CV risks and enable timely interventions. Integrating wearables with AI may remove healthcare barriers and help overcome health disparities.

Another promising avenue to mitigate CVD disparities is the development and utilization of a specialized Large Language Model (LLM), explicitly tailored for CVD consultation and health education. Such a model could offer patients and clinicians access to accurate, up-to-date information, personalizing CVD management [36,37]. By leveraging extensive data and insights derived from clinical studies, patient records and expert knowledge, a CVD-specialized LLM could provide nuanced and contextually relevant responses to patient inquiries, facilitate informed decision-making, and enhance patient education [38]. Such models can deliver personalized guidance, accounting for unique SDOH affecting minoritized populations, including socioeconomic factors, access barriers, and historical healthcare mistrust. Other promising applications of LLMs include integrating with voice assistants to improve communication between patients and clinicians, as currently used for older individuals, adapted for diverse minoritized groups, including Black/African American patients [39]. Additionally, LLMs applied in telemedicine, where patients often struggle to convey critical health information, can help patients articulate symptoms and concerns effectively, ensuring clinicians receive accurate and comprehensive information [40]. Moreover, LLMs can be adapted to the patient's cultural context to provide personalized care coordination, such as sending reminders for taking prescribed medications or engaging in regular physical activity [41]. These culturally-tailored features can empower patients of various backgrounds by fostering consistent adherence to treatment plans and promoting healthier lifestyle choices. These LLM innovations, along with facilitating better communication, delivering patient-centered responses, and encouraging informed decision-making, can expand consistent, high-quality CV care, even in resource-limited settings. Ultimately, by reducing barriers to information, enhancing patient engagement, and supporting clinicians with evidence-based tools, LLMs have the potential to significantly diminish racial and ethnic disparities in CVD outcomes and ensure equitable care for all patients.

1.3. Present realities and future considerations for the use of AI to reduce disparities

The main challenge with AI implementation is bias and underrepresentation, often arising in clinical data entry due to insufficient and incomplete datasets [42]. Unfortunately, AI bias can also be observed within the AI algorithm itself, due to statistical inadequacies and a lack of comprehensive studies [43]. The effectiveness of AI models depends entirely on the quality of the input data, as AI algorithms learn from patterns that already exist. If data are biased, incomplete, or unrepresentative, the algorithm will mirror those deficiencies (Fig. 2). Apart from biased data, there are also biases in AI model sampling, data distribution, healthcare delivery, resource allocation, clinical decision making and treatment [12]. Thus, addressing bias is mandatory to prevent worsening health outcomes for racial and ethnic minority groups. Equally important are the high healthcare costs and lack of acceptance among underrepresented communities, posing significant barriers to successful AI technology implementation, particularly considering a healthcare system already plagued by deep-seated distrust [33,44,45]. Clinicians may struggle to select the suitable AI model for a specific clinical scenario, lack awareness of correct data entry methods, and may be unable to discern system errors or biases that could restrict its relevance for certain patient groups [32,46,47].

To address these challenges, multiple stakeholders must collaborate to establish systems and policies that prevent algorithmic bias and ensure equity, transparency, fairness, and accountability throughout the algorithm life cycle, and trained on accurate and comprehensive data to minimize inefficiencies and promote equitable health resource allocation [43]. Additionally, research must prioritize diverse representation at multiple stages, including cohort selection, training and implementation. The 2023 National Academies of Sciences, Engineering and Medicine Roundtable review on the use of race, ethnicity and ancestry as

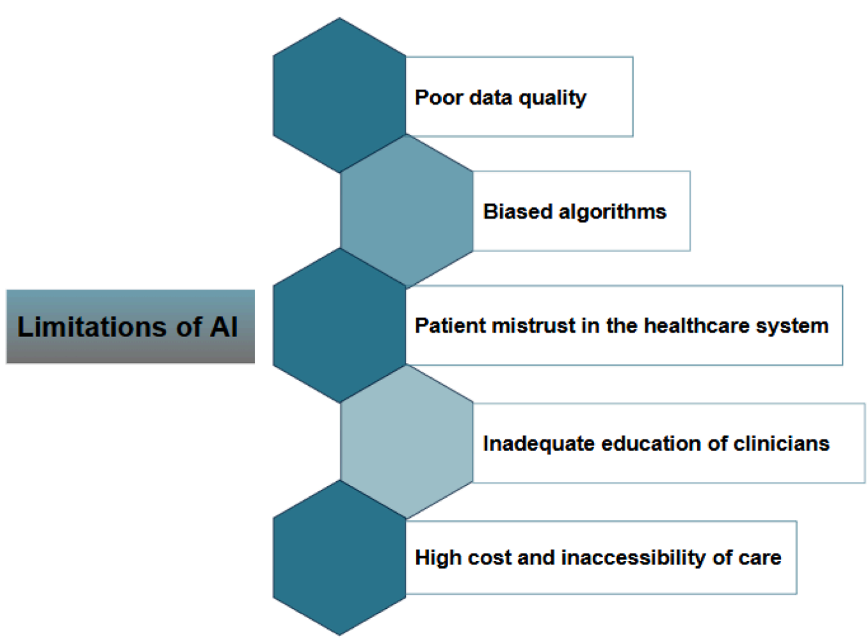
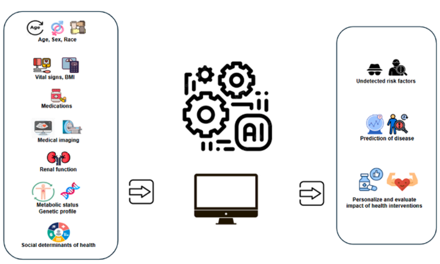


Fig. 2. Limitations of AI include poor data quality, biased algorithms, patient mistrust in the healthcare system, inadequate clinician education, and high cost and care inaccessibility. Figure created by Orakwue, C. Et al.

population descriptors in genomic research highlighted the goal to advance precision health [48]. Furthermore, algorithm models must undergo continuous upgrade as new patient groups are studied and study results are reported, optimizing algorithm performance, expanding accessibility and reducing the risk of inadvertently widening healthcare disparities [33,47]. Finally, clinicians should receive specialized training on proper data entry, selecting suitable AI technology for different clinical scenarios, and recognizing biases that may undermine the relevance of the technology to certain demographics.

2. Conclusion: The need for real solutions to CVD disparities

Racial and ethnic disparities in CVD in the US contribute to persistent mortality gaps among White, Hispanic, Asian, and Black/African American groups. These disparities stem largely from differences in SDOH that profoundly undermine their quality of life. To effectively mitigate the unfortunate and persistent burdens of CVD, key barriers such as food deserts, limited access to health care, low income, inadequate education, and bias in medical treatment must be addressed. Optimistically, AI will powerfully support these efforts, providing innovative ways to identify complex social and health patterns that may not be easily detected, facilitating real-time health monitoring and providing personalized feedback. Nevertheless, overcoming shortcomings in healthcare outcomes will remain challenging. Hopefully, AI may help clinicians and policy makers address social barriers to care for timely and equitable interventions, ultimately decreasing and even eliminating health disparities.



Central Illustration

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We understand that the Corresponding Author is the sole contact for the Editorial process. He is responsible for communicating with the other authors about progress, submissions of revisions, publication and post-publication processes.

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Chisom J. Orakwue: Writing – review & editing, Writing – original draft, Conceptualization. **Farbod Zahedi Tajrishi:** Writing – review & editing. **Constance M. Gistand:** Writing – original draft, Conceptualization. **Han Feng:** Writing – review & editing. **Keith C. Ferdinand:** Writing – review & editing, Writing – original draft, Supervision, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Keith Ferdinand reports a relationship with Boehringer Ingelheim that includes: consulting or advisory. Keith Ferdinand reports a relationship with Medtronic that includes: consulting or advisory. Keith Ferdinand reports a relationship with Novartis that includes: consulting or advisory. Keith Ferdinand reports a relationship with Amgen that includes: consulting or advisory. Keith Ferdinand reports a relationship with Lilly that includes: consulting or advisory. Keith Ferdinand reports a relationship with Janssen that includes: consulting or advisory. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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