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From diagnosis to management: unveiling the challenges of artificial intelligence solutions in cardiovascular healthcare

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Abstract

Background Cardiovascular diseases (CVDs) are the leading cause of mortality in the world. Artificial Intelligence (AI) offers an opportunity to improve the quality of care provided to cardiovascular patients due to its ability to handle large and complex data. Despite promising results obtained in several studies, widespread adoption of AI in cardiovascular care is lacking due to several existing challenges. This study aims to identify and analyze these challenges.

Methods A mixed-methods approach was employed, combining semi-structured interviews with a self-administered online survey. Sequential sampling was used to select participants. Interview data were analyzed using inductive thematic analysis, while survey responses were examined through summary statistics and correlation analysis.

Results A total of 5 interviews were conducted, and 91 valid survey responses were obtained. Survey respondents included doctors, nurses, medical researchers, health IT specialists, hospital administrators, and other clinically affiliated participants working with cardiovascular patients. Eight major challenges were identified: data-related challenges, regulatory challenges, infrastructural challenges, gaps in knowledge, transparency challenges, ethical challenges, change management issues, and acceptance challenges.

Conclusion This mixed-method study finds that the main obstacles to bringing AI into cardiovascular care stem not from algorithmic limitations but from a constellation of data, regulatory, infrastructural and human-factor gaps. Closing these interdependent bottlenecks through coordinated policy, capacity-building and transparent evaluation is therefore essential for translating AI's proven diagnostic promise into routine clinical practice.

Keywords Artificial Intelligence, Cardiovascular care, Machine learning, Challenges, Cardiology, Digital health

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Introduction

Cardiovascular diseases (CVDs) are the leading cause of mortality globally, accounting for nearly 19 million deaths in 2019 [1]. This number is projected to increase due to the aging demographics and the lack of healthcare workers [2]. Artificial Intelligence (AI) offers a path to helping clinicians and healthcare institutions manage the burden of CVDs through risk stratification, early diagnosis, clinical decision support, patient monitoring, and personalized medicine. Some studies have shown promising results in several applications of AI in cardiovascular care [3–9]. Examples of these studies include the use of a machine learning (ML) model to predict the occurrence of in-hospital cardiac arrests and for the risk stratification of occlusive myocardial infarction [8, 9].

Despite these promising results, the adoption of AI in clinical practice is significantly low due to the novelty of the field and the existence of several challenges hindering its adoption [5, 10]. Wubineh et al. [11] identified four main challenges facing AI in healthcare: ethical and privacy issues, limited patient knowledge, concerns about the reliability and trustworthiness of AI technologies, and impact on professional liability. In a survey of 1,013 doctors across various clinical specialties, Pedro et al. [12] identified limited knowledge and minor skepticism about using AI for certain tasks as key challenges in medical care. Other studies have pointed out that infrastructure, data management, data collection, regulatory concerns, and transparency are major challenges slowing the adoption of AI in clinical practice [13–15]. Although CVDs have a significant impact on healthcare, there is a scarcity of experimental studies investigating the challenges associated with adopting AI in clinical cardiovascular care. A mixed-methods study, by Schepart et al. [10], identified the existence of 5 major challenges of AI in cardiovascular care: insufficient knowledge, limited useability, limited funding, inadequate compatibility with electronic health records, and trust issues. However, it is important to note that the scope of the study was confined to cardiologists and health IT specialists. This limitation may not fully reflect the perspectives of the broader healthcare community.

The goal of this study is to better understand the challenges hindering the adoption of AI in cardiovascular care through a mixed-methods study of healthcare workers and stakeholders involved in cardiovascular care. A larger group, comprising doctors, nurses, medical researchers, hospital administrators, health IT specialists, cardiovascular assistants, and other stakeholders in cardiovascular care, was included to provide a more comprehensive view of the challenges faced. Involving a diverse cohort of healthcare professionals provides a multifaceted understanding of the challenges, ensuring that solutions are robust and widely applicable. By understanding these challenges, targeted interventions could be developed to enhance the adoption of AI, ultimately improving patient outcomes in cardiovascular care.

Methodology

Study design

In this study, a sequential mixed-methods research design was employed, beginning with semi-structured interviews of several stakeholders in cardiovascular care, followed by a self-administered online survey of a broader group. Results from the interviews were used to develop the quantitative survey. This approach allowed the capturing of in-depth perspectives from key stakeholders in cardiovascular care and the corroboration of these findings with quantitative evidence from a wider community of healthcare professionals.

Qualitative study

Participant selection and recruitment

Medical doctors, nurses, health IT specialists, clinical scientists, medical researchers, hospital administrators, and cardiovascular AI specialists were eligible to participate in the interviews. The primary inclusion factors were:

- Knowledge of AI in cardiovascular care.
- Over 3 years of experience in cardiovascular care or AI solutions in cardiovascular care.

Participant recruitment was conducted using purposive sampling. This approach was chosen to ensure that the participants could provide in-depth and informed perspectives directly relevant to the research objectives. Eligible participants were recruited and identified by the researcher and invited to participate in the research via email and LinkedIn.

Data collection

A semi-structured interview guide was developed based on an extensive literature review of the challenges associated with AI in medical care. The interview guide was tested on a demographically similar subset of the target population. Feedback from this group led to refinements in question wording and order, optimizing clarity and response efficacy. The interview guide can be found in the supplementary file for this paper. All interviews were conducted online via video conferencing in November 2023. Each interview lasted 30–40 min and involved a single interviewer. The interviewer asked follow-up questions for clarification and to allow participants to elaborate on the responses provided. The interviews were recorded, transcribed verbatim, and inductively analyzed to identify major themes and additional sub-themes.

Data analysis

The transcribed text was subjected to inductive thematic analysis, a qualitative research method in which themes are derived directly from the data without imposing pre-existing theoretical frameworks [16]. This entailed a systematic process of coding the data in multiple rounds, allowing themes to emerge organically from the participants' narratives. Initial codes were generated by reading and re-reading the transcripts. These codes were then grouped into potential themes, that reflected the core meanings evident in the data. These themes were reviewed and refined iteratively, ensuring they accurately represented the views of participants.

Quantitative study

Participant selection and recruitment

Medical Doctors, nurses, health IT specialists, clinical scientists, medical researchers, hospital administrators, and cardiovascular AI specialists were eligible to participate in the survey. A mix of purposive sampling and snowball sampling was used to ensure that participants met the eligible professional criteria and to reach a larger portion of the target population. Participants were invited to participate in the survey via email and LinkedIn.

Data collection

A 10-minute online survey was created using Soscisurvey (Version 3.5.00) developed by SoSci Survey GmbH based on the key themes identified in the qualitative analysis. The questionnaire was developed in English and pretested with 7 individuals who were demographically similar to the target population. Feedback from the pretest indicated that certain questions in the survey were ambiguous and lacked clarity. Consequently, the highlighted questions were refined to be more precise and understandable. The questionnaire included 4 primary sections. The first section provided an introduction to the survey, including consent for data analysis. The second section collected demographic information on job description and geographical location. The third section focused on challenges and perceptions regarding AI in cardiovascular care, with subsections organized around the key themes identified from the interviews. The final section, titled *Notes*, provided participants with an opportunity to contribute additional thoughts and insights that were not covered by the structured survey questions. The final questionnaire can be found in the supplementary file for this paper.

To ensure data quality and the attentiveness of respondents, a screener question was included in the survey. The screener was designed to filter out inattentive or disengaged participants who might compromise the reliability of the survey results. Specifically, the screener question asked participants to select a specific answer to confirm their attentiveness. The question was phrased as follows:

"*The topic of this survey is related to Artificial Intelligence in Cardiovascular Diseases. However, this question is an attention checker. Please select 'Neutral' from the options below.*"

Responses to this screener question were carefully monitored, and any participants who did not follow the instruction were flagged as inattentive. These responses were subsequently excluded from the final analysis to ensure that only data from fully engaged and attentive participants were considered.

The survey link was shared with the participants and was online for 6 weeks from November to December 2023. The survey results were subsequently downloaded in Comma-Separated Values (CSV) format and subsequently analyzed.

Sample size calculator

To ensure the statistical power of the survey, the required sample size was determined using the SurveyMonkey sample size calculator. The calculation parameters included a population size exceeding 1 million, reflecting the global and diverse pool of eligible respondents. A 95% confidence level and a 5% margin of error were applied to achieve reliable and statistically significant results.

The calculator indicated that a sample size of 385 respondents would be optimal for achieving robust statistical results. This sample size was chosen to effectively balance the risk of Type 1 and Type 2 errors, aiming to achieve a statistical power of 80%. This power level means there is an 80% chance of detecting a true effect if it exists, thus enhancing the reliability of the findings and the ability to make valid inferences from the survey data [17].

Data analysis

The data was initially cleaned to remove incomplete responses and responses that incorrectly answered the screener. As responses were numerically coded automatically by the survey platform, additional coding was not necessary. Descriptive statistics were employed to gain insights into the characteristics of respondents and for univariate analysis. Given that purposive sampling and snowball sampling were employed to recruit participants, the resulting dataset was not normally distributed. To account for the non-normality of the data, non-parametric statistical tests, which do not assume normal distribution, were used. Specifically, the Kruskal-Wallis test was used for comparing more than two independent groups as it is a robust alternative to the one-way ANOVA when the assumption of normality is lacking [18]. For pairwise comparisons, the Mann-Whitney U test was selected due to its effectiveness in handling ordinal data and non-normal distributions [18]. To control for Type I errors in multiple comparisons, the Bonferroni correction was applied, adjusting the p-value threshold to maintain a significance level of $p \leq 0.05$. Additionally, a multinomial logistic regression was employed to evaluate the effects of job description, location, and knowledge of AI on perceptions of AI's impact on the diagnosis and management of CVDs. The analysis was done using Python libraries: Pandas (version 1.4.2) [19, 20], SciPy (version 1.8.1) [21], NumPy (version 1.23.3) [22], Statsmodels (version 0.14.0) [23], and Scikit-learn (version 1.3.2) [24] due to their versatility, efficiency, and extensive capabilities for handling and analyzing large datasets. Statistical significance was set at p-value ≤ 0.05.

Qualitative results

Description of participants

Five experts (PT1–PT5) representing diverse sectors within the cardiovascular care domain were interviewed, bringing perspectives from clinical medicine integrated with AI research (PT1), industry development of AI solutions for cardiovascular disease (PT2), scientific investigation into cardiovascular care (PT3), digital-health implementation in hospital settings (PT4), and AI-supported cardiovascular interventions (PT5).

Identified challenges

Eight major challenges were identified by participants during the interviews. The findings are summarized in Table 1 and described below.

1. *Data-Related Challenges*: Participants identified several issues related to data that existed and needed to be addressed. According to them, data is vital for training AI algorithms in cardiovascular care. However, challenges such as data integration and access were prominent concerns. Participants noted that while data for training AI models is theoretically available in various cardiovascular institutions, practical access is hindered by several factors. These include data fragmentation, the existence of data silos, regulatory differences, inconsistencies in data annotation, and differences in regulation, which make accessing this data difficult. Participants also highlighted that cardiovascular care requires multimodal data for the diagnosis of CVDs. However, they highlight that existing AI solutions do not allow for the integration of multimodal data in the course of treatment and this poses a challenge to their use in cardiovascular care.
2. *Regulatory Challenges*: Participants also highlighted unclear regulations and the inflexibility of existing regulations as the primary regulatory challenges to AI in cardiovascular care. They stated that existing AI regulations are vague and do not have specific medical or cardiovascular applications. This lack of clarity results in a long and arduous process for obtaining regulatory approval for AI solutions in cardiovascular care. Additionally, participants indicated that existing regulations require developers to freeze their algorithms to obtain regulatory approval and developers have to apply for a new approval once changes are made to the algorithms. Participants believed that this poses a challenge as AI algorithms require constant training with real-world data to be safer and more efficient. Requiring regulatory approval each time an algorithm is trained results in an overly burdensome process.
3. *Infrastructural Challenges*: Participants also acknowledged the dearth of human and technological infrastructure for the integration of AI in cardiovascular care. The necessity of having personnel with the appropriate expertise to develop and manage AI infrastructure was highlighted as essential for effective clinical application. However, they also suggested that most healthcare institutions lack the necessary IT department, equipped with an understanding of how AI systems work. Concerns were raised about healthcare facilities relying on legacy systems that do not align with modern AI technology, which is believed to impede AI's integration into cardiovascular care. A rural-urban divide in infrastructure was also noted, with large urban healthcare institutions actively pursuing AI advancements, whereas rural counterparts are often less engaged in developing AI infrastructure.
4. *Knowledge Challenges*: Participants highlighted a bidirectional knowledge gap between healthcare professionals and developers. They noted that healthcare professionals lack sufficient understanding of AI to effectively communicate its mechanisms to patients, while developers often lack the medical expertise necessary for creating clinically relevant applications. The lack of AI training in medical and medically-affiliated curricula was highlighted as one of the primary reasons for this gap. However, they also acknowledged the existence of advanced professional courses for individuals willing to improve their knowledge of AI.
5. *Transparency Challenges*: A lack of explainability of existing AI solutions was identified as a primary challenge of AI in cardiovascular care by participants. They indicated that the transparency of AI models is key for legal and liability protection and existing AI models in cardiovascular care do not offer sufficient explanation of their decision-making process and functionality. They acknowledged that

Table 1 Challenges of AI in Cardiovascular Care

Main Theme	Sub-Theme	Quotes from Interview Participants
Data	Data access	*"The first one is access. Training an AI model requires a lot of data and it is very difficult in many cases to acquire a lot of data"- PT1* *"Data is key for training AI algorithms and having sufficient data for training is one of the key challenges" - PT2*
	Data integration	*"Another challenge lies in connecting data points, so not just integrating EHR data with ECG data, imaging data, vital signs, and voice analysis. So not just looking at one data source but interpreting everything in the context of another"- PT1*
Regulations	Unclear regulations	*"Regulatory approval for medical AI is more complex. The process is often long and requires evidence that the AI's recommendations are at least as good as, if not better than that of a human expert."- PT5*
	Static regulations	*"Another problem is that regulatory bodies ask AI companies to freeze their algorithms for approval. I think this is a bit of a hurdle and also an inconsistency because they want safer and better products but then they hinder them because they don't know how to or because they require freezing." - PT1*
Infrastructure	Lack of infrastructure	*"The infrastructure, in terms of know-how and competency of staff, the technology, the service, and performance, is largely missing for AI in cardiovascular care." - PT4* *"Many healthcare facilities use legacy systems that aren't readily compatible with the latest AI technology"- PT5*
	Rural-urban divide	*"At this stage, AI progress is concentrated on large university hospitals or well-equipped hospitals, and on the startup market in urban areas, but not in the outskirts or rural areas." -PT5*
Knowledge	-	*"When I spoke to some healthcare workers, I noticed they didn't know anything. They hadn't even tried ChatGPT and had no hands-on experience with AI. This is one side of the spectrum"- PT4* *"I see that there is some knowledge available on what it means. The basic terms are quite common these days, like on convolutional neural networks, but most people have limited understanding of what it means."- PT2* *"We generally see a lack of education and training on how to work with AI, or interpret its recommendations."- PT5*
Transparency	-	*"One of the major challenges is explainable AI and understanding machine reasoning and also in terms of legal issues and liability. This is still one of the biggest hurdles that must be defined and needs to be understood."- PT2* *"There is a black-box phenomenon for different AI solutions in healthcare. This black-box phenomenon- you can't have it in medical treatment."- PT4*
Ethics	Fairness	*"Of-course there is the issue of biases in terms of patient recruitment for training data. I think there are some good practices that need to be followed in order to ensure that the training datasets are representative of the population that is being treated or diagnosed. So, I think that's an aspect that needs to be accounted for"- PT1.*
	Responsibility	*"There is the question of accountability when AI is used in diagnosis and treatment- Who is responsible if something goes wrong?"- PT5.*
	Accountability	*" Even though we have dedicated guidelines indicating and structuring how data treatment should be performed, some care providers do not follow these recommendations or report the model development process"- PT2.*
Change Management	Impact analysis	*"Medical and economic impact is the core of digital health and also AI models. We have to quantify what we bring from a medical perspective and an economic perspective"- PT3* *"Regarding the impact measurement, I rarely see complete views. I call this the net present value. It's basically a comprehensive view on what the algorithm does and what the whole infrastructure requires"- PT3*
	Plans	*"Certainly, change management is obligatory, especially when introducing a new way of working in clinical practice. One of the major challenges is not the technical part but how to introduce new solutions to an established way of working, that fits in clinical practice without an extra cost. Most healthcare institutions lack this plan"- PT2*
Acceptance	-	*"Minor barriers could be acceptance by patients, and physicians. People are interested and believe that the technology can do better but there are still people that don't want their data analyzed or stored."- PT1* *"Experts in their field have an established way of working and some of them are struggling with new techniques and not seeing AI as a threat"- PT2* *"Healthcare professionals may be skeptical or uncomfortable relying on AI for decisionmaking. This resistance can stem from concerns about job security, or doubts about AI capabilities."- PT5*

explainability is also key for regulatory compliance and entry into healthcare. Hence, the existence of black-box models does not spark confidence among clinicians and regulators, which results in slower adoption in clinical practice.

6. *Ethical Challenges*: Participants highlighted fairness in data collection, lack of accountability, and vagueness of responsibility as the primary ethical challenges faced by AI in cardiovascular care. They indicated that training datasets used in the development of AI solutions are not representative of the target populations. Hence, this lack of representation means that the biases inherent in the training data are likely to be replicated and even amplified in the AI models. They acknowledged that this could potentially lead to unequal or suboptimal outcomes for underrepresented groups. Concerns about responsibility were identified as a significant barrier to integrating AI into clinical care. Participants noted that traditional medical care typically assigns responsibility to clinicians for negative outcomes, but this responsibility is less

clearly defined when AI algorithms are involved in decision-making. Hence, reluctance exists amongst clinicians on the use of AI in cardiovascular care. Participants also believed that AI developers are not transparent enough in reporting the developmental process and the steps leading to the creation of the final product. They indicated that this lack of accountability diminishes the trust of clinicians and their willingness to adopt AI solutions in cardiovascular care.

7. *Change Management Challenges*: Participants acknowledged the lack of quality change management plans and the lack of medical and economic impact analysis for AI solutions. They believed that the integration of AI in cardiovascular care is significantly slowed as healthcare institutions lack a comprehensive and coherent plan on how to integrate AI in cardiovascular care. According to the participants, a critical component of effective change management plans is impact analysis, which they noted as being inadequately addressed. They observed that the current impact analyses lack the depth necessary to provide meaningful insights into the effects of AI on both clinical care and administrative processes. According to them, the absence of well-defined change management plans poses significant challenges for both medical institutions and governments in effectively integrating AI solutions into cardiovascular care.
8. *Acceptance Challenges*: Participants acknowledged that acceptance by healthcare professionals and patients was a key factor in the integration of AI in cardiovascular care. They noted that skepticism exists among healthcare professionals regarding the use of AI in cardiovascular care. This skepticism stems from a reluctance to alter established practices, concerns about job security, and a lack of trust in AI solutions. Participants noted that while this is not the majority opinion, the minority view still significantly affects the integration of AI in cardiovascular care.

Quantitative results

Description of participants

A total of 134 individuals initiated the survey, out of an estimated 700 individuals reached through the purposive and snowball techniques. Of the 134 individuals who initiated the survey, 94 (70.1%) completed the survey in its entirety. However, three participants (3.2% of completed surveys) provided incorrect responses to the screener and were subsequently excluded from the analysis. The decision to exclude three participants who provided incorrect responses to the screener was made to maintain data integrity and ensure the reliability of the study findings. Thus, a total of 91 valid responses were obtained for analysis. Although the majority of participants ($n = 55$, 60.4%) were doctors, the responses also included nurses, medical researchers, health IT specialists, hospital administrators, medical assistants, and cardiovascular technologists. The distribution of participants across different job descriptions is visualized in Fig. 1. The majority of participants were from Europe ($n = 56$, 61.5%), followed by Africa ($n = 24$, 26.4%), Asia ($n = 7$, 7.7%), and North America ($n = 6$, 6.6%). Notably, no responses were received from Australia or South America.

Participants were also asked about their frequency of using AI for work. The responses indicated that 42.6% ($n = 38$) reported never using AI, 23.6% ($n = 21$) reported monthly usage, 16.9% ($n = 15$) reported weekly usage and another 16.9% ($n = 15$) reported daily usage.

1. *Data-related Challenges*: In terms of data access, the majority of respondents (51.5%) reported encountering difficulty (45.3% found it difficult, while 6.2% found it very difficult) in accessing cardiovascular health data for AI analysis and interpretation. 1.6% found data access to be very easy and 12.5% found it to be easy. 34.4% of respondents maintained a neutral position on data access. A pairwise comparison with Kruskal Wallis test indicated the presence of a statistically significant correlation [H [4] = 9.10, $p = 0.028$] between the frequency of use and the opinion regarding data access. Further exploration with *post-hoc* Mann-Whitney test with Bonferroni correction indicated the presence of a statistical difference ($p = 0.038$) in data access views between daily AI users and monthly AI users. Figure 2 shows a box plot visualization in which daily AI users consistently rated data access as more challenging, compared to the more varied responses of monthly AI users. On the compatibility of different data sources for CVD analysis, 36.5% indicated that data sources for CVD analysis were incompatible (4.8% found them highly incompatible and 31.7% found them incompatible). 36.5% maintained a neutral position while 23.8% and 3.2% found data sources for CVD care to be compatible and highly compatible respectively.

2. *Regulatory Challenges*: To measure the clarity of existing regulations for AI solutions in cardiovascular care, participants were asked about the transparency and comprehensibility of existing regulations. The majority of respondents (55%) indicated that existing regulations were not transparent or comprehensible (41.7% expressed disagreement and 13.3% expressed strong disagreement). 35% maintained a neutral position and 10% agreed that existing regulations were transparent and comprehensible. Notably,

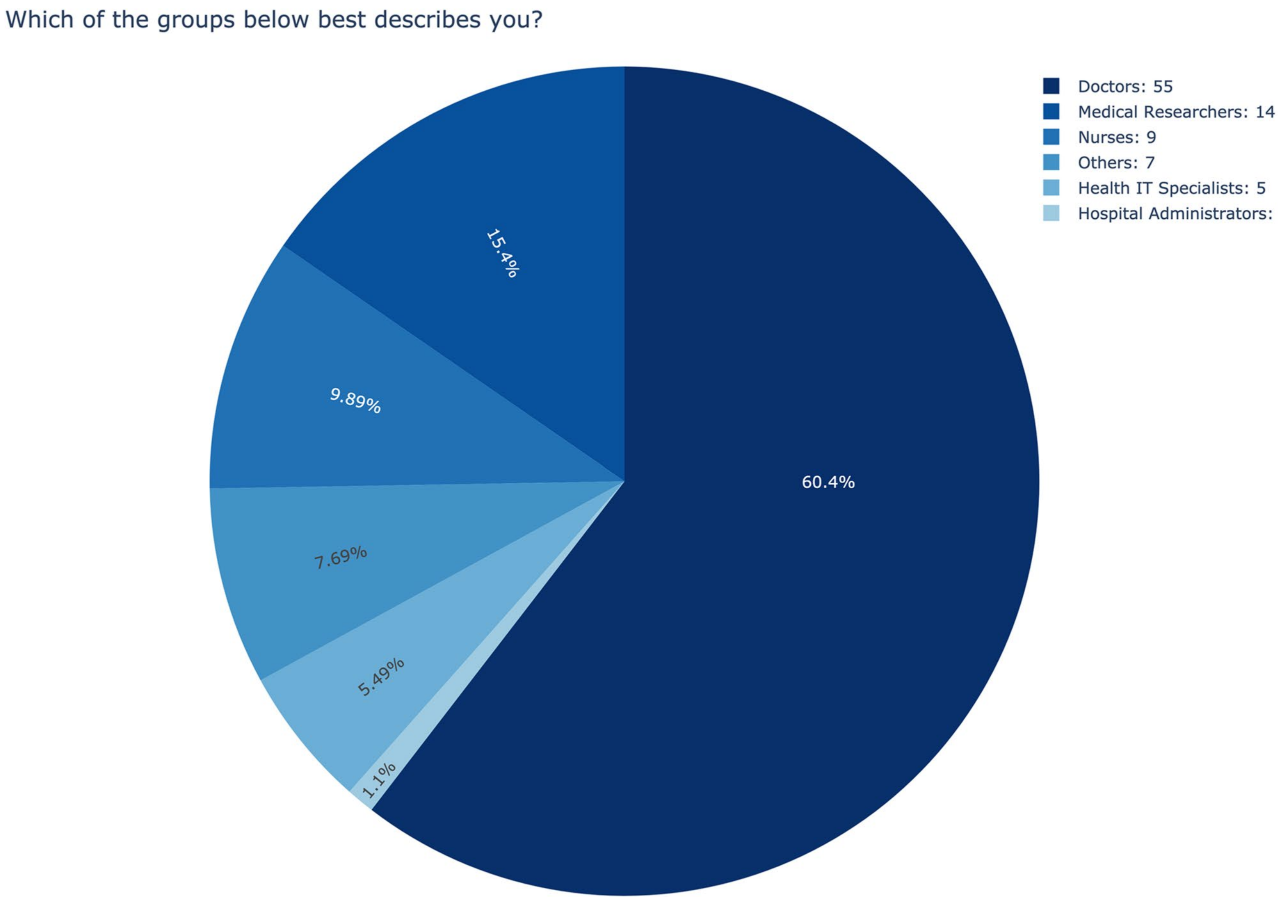

Fig. 1 Job Distribution of Survey Participants

no participant expressed strong agreement. Participants were also asked about the adequacy of the current regulatory framework in facilitating the safe and efficient implementation of AI solutions in cardiovascular care. 40.7% and 5.1% expressed disagreement and strong disagreement with the notion that existing AI regulations were adequate. 37.3% remained neutral and 16.9% expressed agreement. Notably, there were no participants who strongly agreed. The pairwise comparison found no significant relationship between opinions on regulatory clarity and job description ($p = 0.630$) or location ($p = 0.283$). However, there was a significant relationship between opinions on regulatory adequacy and location ($p = 0.007$), though no significant correlation was found with job description ($p = 0.221$). Further post-hoc analysis revealed a significant difference ($p = 0.023$) in views on regulatory adequacy between participants in Europe and those in Africa.

3. *Infrastructural challenges*: Regarding organizational readiness for dealing with the introduction of AI in cardiovascular care, 24.7% of respondents indicated that their organizations were not at all equipped. 39.3% and 30.2% of respondents considered their organizations to be slightly equipped and moderately equipped respectively. Only 5.6% indicated that their organizations were very equipped. Notably, none of the participants regarded their organizations as extremely equipped. The pairwise comparison showed a significant difference [$H(3) = 7.893$, $p = 0.048$] in organizational readiness based on geographical location. *Post-hoc* analysis indicated a marginal difference ($p = 0.063$) between the respondents in Europe and Africa. The boxplot visualization in Fig. 3 shows that respondents from Africa consistently indicated lower levels of organizational readiness compared to the varied responses of respondents in Europe.

4. *Knowledge Challenges*: The question asking participants to rate their knowledge of AI revealed that the majority (68.2%) had less than optimal levels of knowledge: 3.3% had very poor knowledge, 18.7% had below-average knowledge, and 46.2% had average knowledge. The frequency and distribution of participants' knowledge levels are shown in Fig. 4. Additionally, participants were asked if they

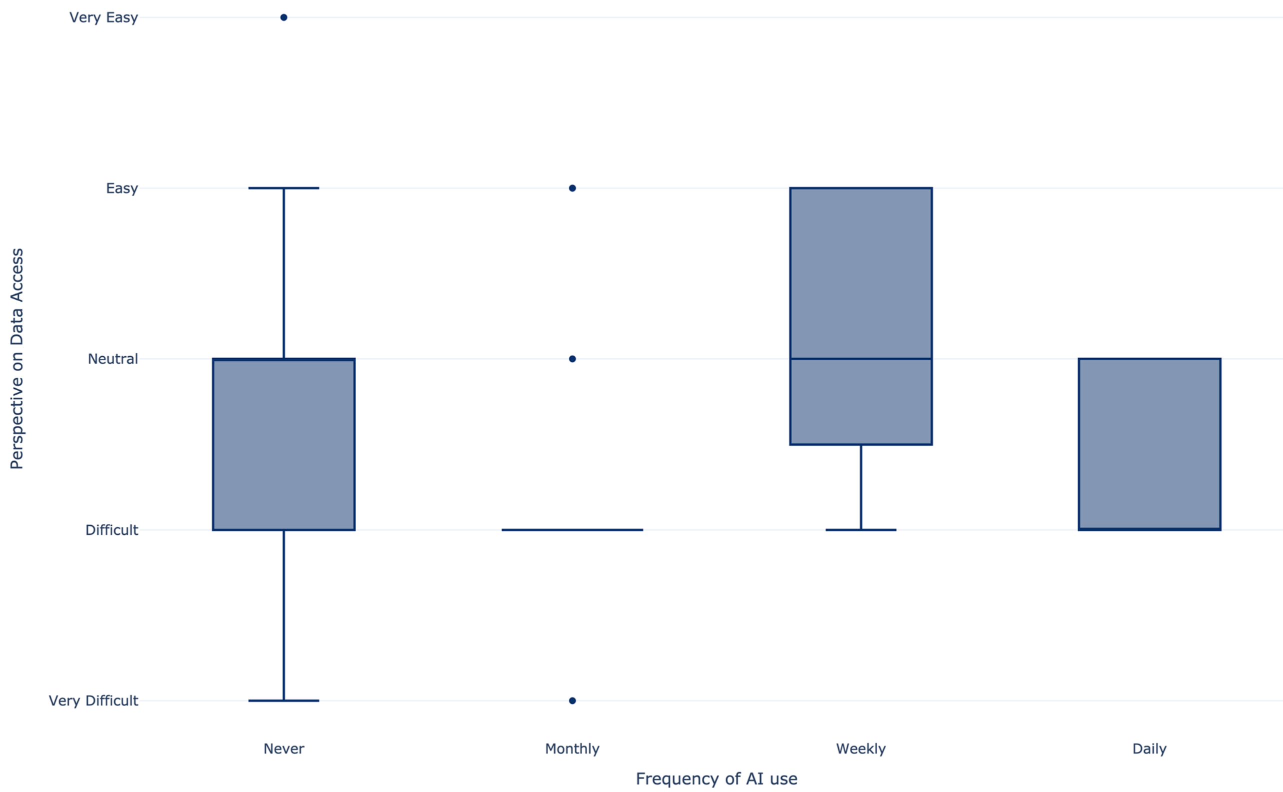

Fig. 2 Comparison of Participant Views on Data Access by AI Use Frequency

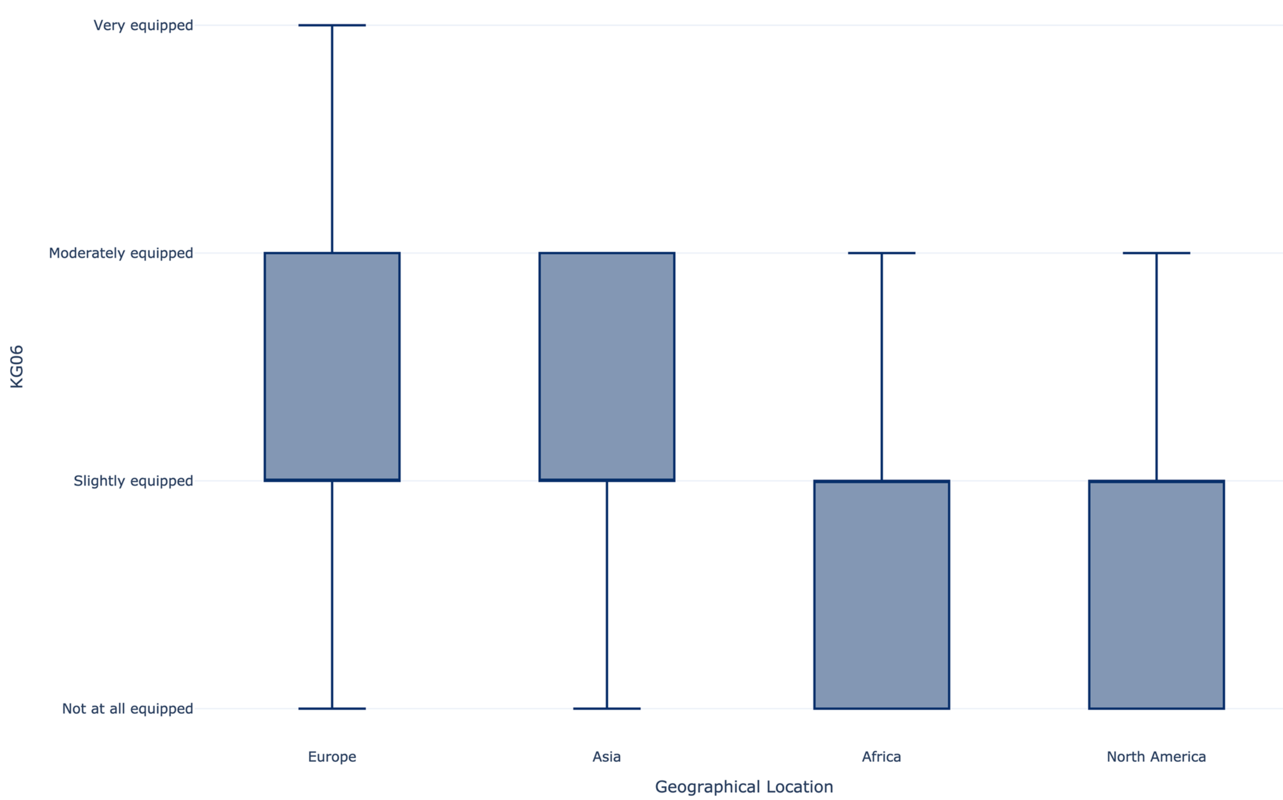

Fig. 3 Comparison of Organizational AI Readiness by Location

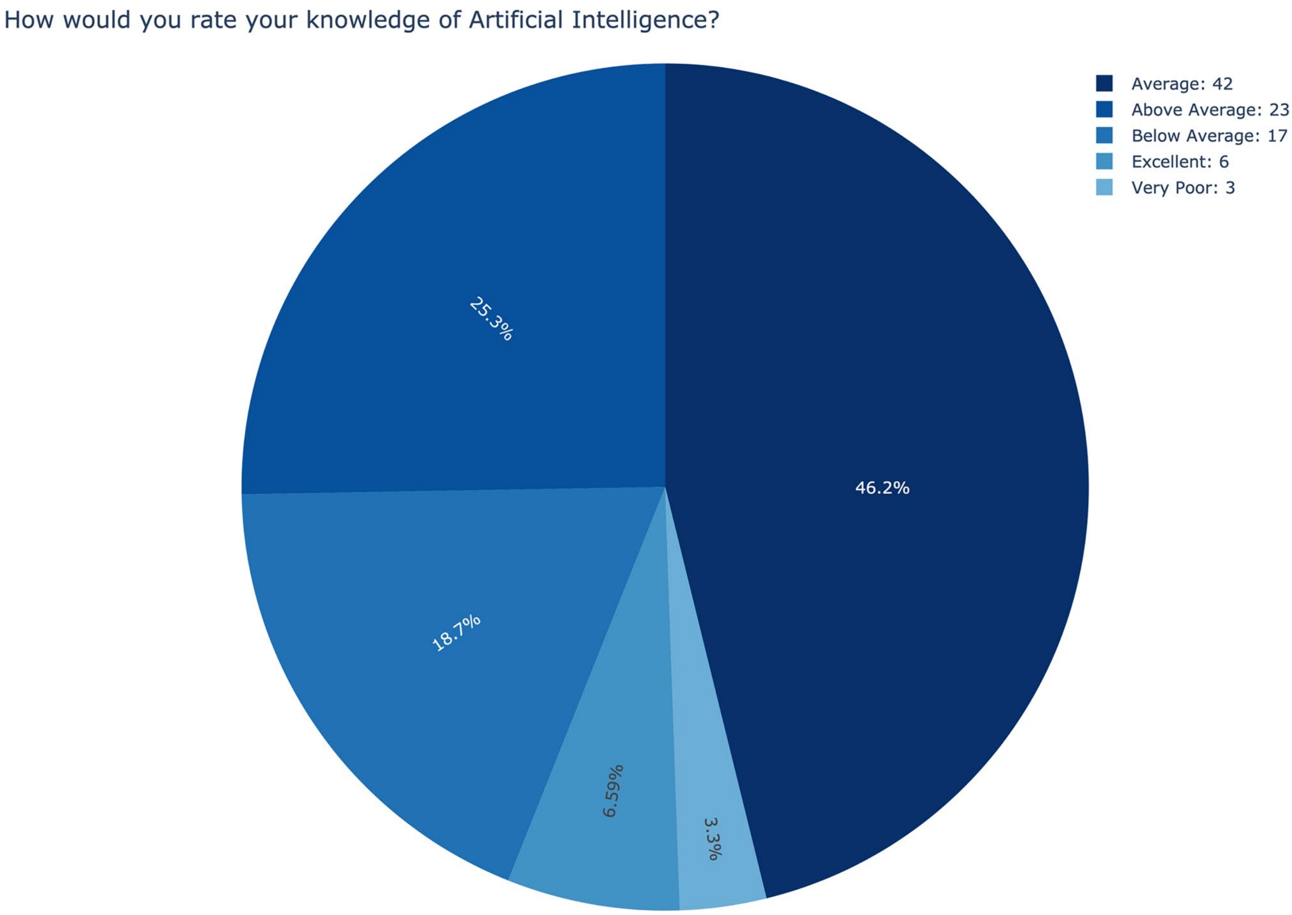

Fig. 4 Distribution of AI Knowledge Levels among Survey Participants

would be willing to take courses to improve their knowledge of AI. 78% of respondents were willing to take courses to improve their knowledge of AI, 7.7% were not willing to take additional courses and 14.3% were unsure.

5. *Transparency Challenges*: Regarding the importance of transparency, 82.4% of respondents believed that AI systems should offer some form of explainability in their decision-making process, with 50.5% agreeing and 31.9% strongly agreeing. In contrast, 12.1% were neutral, while 4.4% disagreed and 1.1% strongly disagreed. Furthermore, on the impact of transparency on user trust, 62% of respondents felt that understanding the clinical decision-making process of AI systems was necessary to trust their recommendations. Specifically, 36.3% agreed, and 26.4% strongly agreed. Conversely, 20.9% of respondents did not perceive understanding the decision-making process of AI systems as impactful on their trust in their recommendations. Specifically, 15.4% disagreed and 5.5% agreed. 16.5% of respondents were neutral.
6. *Ethical Challenges*: On fairness, participants were asked about the importance of AI solutions considering patient diversity in cardiovascular care. The majority of respondents (52.2%) considered it extremely important for AI solutions to consider patient diversity. 18.9% considered it to be important and 18.9% maintained a neutral position. 6.7% and 3.3% of respondents considered it to be slightly unimportant and not important at all respectively. Subsequently, participants were asked if existing AI solutions adequately addressed the diversity of the patient population. 10.2% of participants responded in the affirmative, 38.6% maintained a neutral position and 51.2% responded in the negative.
7. *Change Management Challenges*: 30.3% and 34.2% of respondents considered having an organizational plan for the integration of AI in cardiovascular care to be important and extremely important respectively. 19.7% of respondents took a neutral position. 10.5% and 5.3% indicated that having a plan was slightly unimportant and not important at all respectively. When asked about the quality of their organizational plans for the integration of

AI in cardiovascular care, none of the respondents indicated that their organizational plans were fully optimized and comprehensive. 6.6% and 19.7% indicated that their organizational plans were well-developed and moderately developed respectively. 34.2% indicated that their organizational plans were poorly developed while 39.5% indicated that their organizational plans were non-existent.

8. *Acceptance Challenges*: Participants were asked several questions to gauge their perspective of AI. Figure 5 contains a comprehensive overview of the distribution of responses. In the multinomial logistic regression model, none of the predictors- job description ($p = 1.000$), location ($p = 0.520$), and AI knowledge ($p = 0.474$)– showed a statistically significant effect on the belief that AI would improve CHD diagnosis and management.

Discussion

This mixed-methods study was conducted to identify the gaps in AI solutions for the diagnosis and management of CVDs. The interviews and surveys included diverse health professionals involved in the care of cardiovascular patients. This diverse group was selected to offer a comprehensive view of the challenges. To my knowledge, this is the first study to assess such a diverse group of health professionals in cardiovascular care. In the interviews, several gaps were identified that aided the development of the ensuing quantitative research. Specifically, participants identified data-related, regulatory, infrastructural, knowledge, transparency, ethical, change management, and acceptance challenges. Identifying these gaps underscores the complexity of integrating AI solutions into the diagnosis and management of CVDs.

Data-related challenges

On data, participants highlighted the critical role of large datasets in the implementation of AI in cardiovascular care. However, they also pointed out that challenges related to accessing this data and integrating data from different sources persist. Large datasets are essential for training robust AI models in cardiovascular care, as they enable the algorithms to learn from a diverse range of patient profiles and clinical scenarios, thereby improving the model's generalizability and accuracy [25, 26]. The qualitative findings on data access were reinforced by a larger survey, which found that a majority of participants experienced some difficulty with data access. These findings align with other studies involving healthcare workers in Europe, which also highlight the challenges of implementing AI in healthcare broadly [27, 28]. However, these studies additionally identify legal barriers as the primary reason for difficulties with data access. The survey also revealed that a greater use of AI amplifies the challenges associated with accessing the data required for AI development. On data source compatibility, the responses of

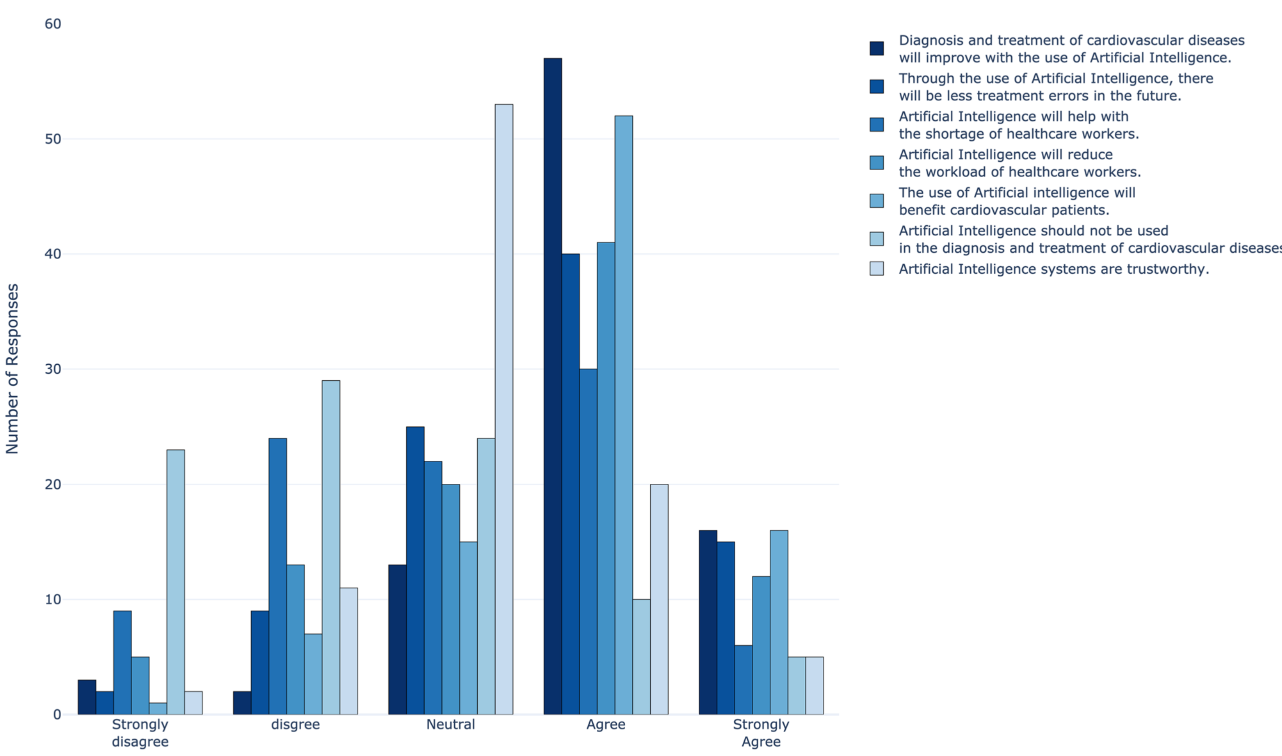

Fig. 5 Survey Participants' Views on AI

participants were more varied. A substantial portion of respondents indicated the presence of compatibility issues and a little under a third of respondents found data sources to be compatible, indicating a diversity of experiences on this issue. Additionally, the significant portion of neutral responses may indicate a lack of familiarity with data compatibility issues, underscoring the need for targeted educational initiatives to better equip healthcare professionals with the necessary knowledge.

Regulatory challenges

Unclear and static regulations were identified by interviewees as the primary regulatory challenges in integrating AI into cardiovascular care. They also noted that these challenges impede the seamless integration of AI. The lack of clarity in regulations was corroborated by the survey, which found that the majority of respondents believed the existing regulations were neither transparent nor comprehensible. Over a third of respondents maintained a neutral position indicating the absence of strong opinions or the lack of sufficient knowledge on the topic. Additionally, a significant portion of respondents also indicated that existing regulations are not adequate to facilitate the safe and efficient implementation of AI solutions in cardiovascular care. The significant relationship between opinions on regulatory adequacy and location, particularly the notable difference between Europe and Africa, suggests that regional regulatory environments may influence perceptions of AI's regulatory requirements. This finding underscores the need for region-specific regulatory frameworks that address local concerns and facilitate more consistent integration of AI in cardiovascular care. The findings of this study echo findings by Rajpurkar et al., who noted that "Traditionally, regulators of AI systems approve only one locked set of parameters, yet this approach does not account for the necessity to update models, as data evolve due to changes in populations, data collection tools, and care management" [29]. Existing literature has identified the primary reason for the lack of clarity in AI regulations for healthcare as the conflict between the data-intensive nature of algorithms and existing data privacy regulations [30, 31]. Further research is needed to identify the specific gaps in current regulatory frameworks and explore how adaptive regulatory models can be developed to better support the integration of AI in cardiovascular care.

Infrastructural challenges

Successful integration of AI in healthcare requires both advanced technological tools and trained personnel capable of leveraging these technologies effectively [32]. Interviewees indicated that existing healthcare institutions lacked the necessary human and technological infrastructure for the successful integration of AI in cardiovascular care. They also highlighted a significant rural-urban divide in infrastructure access, potentially driven by disparities in funding, resource allocation, and facility capabilities. Given the established rural-urban divide in cardiovascular health outcomes [33–35], addressing these infrastructure disparities is crucial. Ensuring equitable access to advanced AI technologies might help mitigate health disparities and improve cardiovascular care across different regions. The survey results, which revealed that over 90% of respondents felt their organizations were inadequately equipped, reinforce these concerns. Additionally, several studies have identified technological deficits as a significant challenge in the implementation of AI in healthcare [10, 11, 27]. This underscores the need for robust and adaptable infrastructure to support AI adoption effectively. The lower levels of organizational readiness reported by participants in Africa compared to Europe highlight the need for location-specific strategies to overcome infrastructure challenges and enhance AI integration.

Knowledge challenges

Interviewees also indicated a prevalent knowledge gap between healthcare professionals and developers. They indicated that medically-affiliated curricula lack relevant AI-related training. Hence, medical professionals lack the necessary understanding of AI to effectively work with it or communicate its mechanisms to patients. Exploring the reasons behind the absence of AI-related training in medical curricula would provide valuable insights into the systemic challenges contributing to the knowledge gap. For instance, competing educational priorities, such as the need to cover traditional medical subjects extensively, and a shortage of faculty with expertise in AI, may contribute to this gap. In the survey, the majority of participants reported having a moderate or below-average understanding of AI. These survey results reinforce the interview findings, highlighting a knowledge gap that could hinder effective collaboration between healthcare professionals and AI developers. These findings align with other studies that highlight limited AI knowledge among healthcare professionals [10, 36, 37]. While a general awareness of AI is present, these studies emphasize that the main deficiency lies in a deeper understanding of AI mechanisms, which hinders professionals' ability to effectively explain AI-related concepts to patients. The survey also revealed that the majority of respondents were willing to take additional courses to improve their knowledge of AI. This willingness represents an opportunity to develop targeted educational programs that could bridge the knowledge gap and enhance the effective integration of AI in clinical practice.

Transparency challenges
Interviewers highlighted the existence of transparency gaps with the prevalence of unexplainable models impacting the level of confidence among clinicians and regulators. Transparency gaps refer to the inability of AI systems to provide clear, understandable explanations for their decision-making processes, often resulting in what are known as 'black-box' or 'unexplainable models' where the logic behind AI recommendations is unclear to clinicians [38]. Although survey respondents overwhelmingly agreed on the importance of explainability, there was a little less consensus on whether the explainability of AI impacts their level of trust in the recommendations offered by these solutions. Furthermore, while the survey results do not explicitly confirm the existence of transparency challenges, they reveal that consensus has not been achieved on the impact of transparency or the level of transparency required for fostering trust in AI recommendations. The interview findings align with those of other studies that highlight significant transparency gaps in AI systems [10, 39]. However, unlike the survey results, these studies demonstrate that transparency overwhelmingly influences healthcare professionals' ability to trust AI recommendations. The mixed responses from survey participants suggest that while the importance of explainability is widely acknowledged, other factors—such as demonstrated accuracy or clinical outcomes—may play a more significant role in determining the level of trust clinicians place in AI recommendations.

Ethical challenges
The interviews revealed that the primary ethical challenges in AI include fairness in data collection, lack of accountability, and ambiguity regarding responsibility. Participants indicated that these issues significantly affect the trust healthcare professionals place in AI solutions. Bias in data collection not only affects fairness but also leads to faulty models, as these biases are replicated in the model outputs [40]. The survey results show that healthcare professionals understand the importance of fairness for AI solutions. However, they also indicate that existing solutions often fail to adequately address fairness concerns across diverse patient populations. These findings are consistent with other studies that have identified significant biases in medical AI algorithms [41, 42]. Furthermore, these studies have highlighted issues such as inadequate data fairness, lack of diverse data, ambiguous guidelines, and limited understanding as key factors contributing to these biases. Future research should explore strategies for enhancing accountability through comprehensive AI auditing frameworks and developing fairness-aware algorithms to address biases in data collection, ensuring equitable patient representation and trust in AI-driven healthcare systems.

Change management challenges
Interviewees also indicated the lack of quality change management plans and the lack of medical and economic impact analysis as key change management challenges for AI in cardiovascular care. A quality change management plan involves structured strategies for integrating new technologies, managing training needs, and addressing stakeholder concerns [32]. Without such plans, healthcare institutions may experience disorganized adoption processes, reduced staff enthusiasm, and disruptions in clinical workflows [43, 44]. Additionally, the absence of comprehensive medical and economic impact analysis undermines stakeholder confidence by failing to demonstrate the potential benefits and risks of AI solutions [43]. Survey results align with these findings, indicating that while the majority of respondents recognize the importance of having a well-developed organizational plan, many report that their institutions' plans are either non-existent or insufficiently developed. Future research needs to explore the unique requirements and challenges of AI change management plans and impact analysis in healthcare settings, particularly in comparison to the protocols and considerations involved in the introduction of new medications.

Acceptance challenges
Interviewees also indicated the existence of some skepticism amongst end users for AI solutions in cardiovascular care. They highlighted that although this skepticism was not the majority position, it was impactful as overwhelming acceptance is required for the introduction of AI in cardiovascular care. Survey results corroborate these findings by showing that while most respondents held positive views on AI's potential impact on diagnosis, treatment errors, worker shortages, and patient benefits, a significant number maintained a neutral stance on the trustworthiness of AI solutions. Furthermore, approximately one-sixth of respondents expressed reservations about the use of AI in cardiovascular care, revealing a notable divergence of opinions within the surveyed population. This divergence indicates that while there is general support for AI, targeted efforts are needed to address specific concerns and improve overall acceptance. While this skepticism did not constitute the majority view, its presence is crucial, as even a small proportion of skepticism can hinder the widespread acceptance and implementation of AI in cardiovascular care. The multinomial logistic regression analysis, which found no significant effect of job description, location, or AI knowledge on beliefs about AI improving CHD diagnosis, suggests that perceptions of AI's potential may be influenced by factors beyond these predictors. This underscores the need for further exploration into what drives varying levels of support for AI in cardiovascular care. Despite recognizing

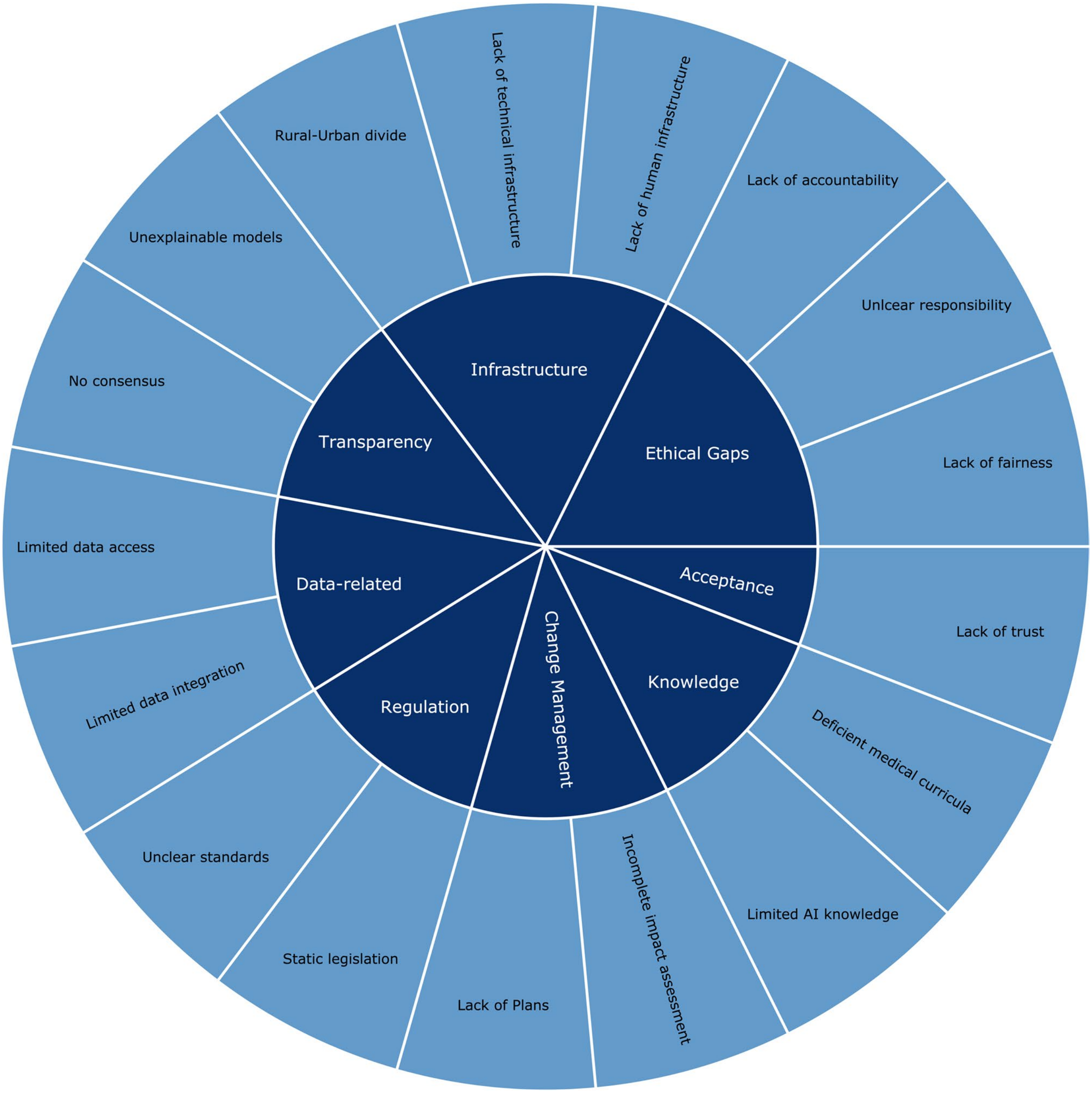

Fig. 6 Overview of Findings on Challenges of AI in Cardiovascular Care

the challenges associated with AI, participants' generally optimistic views align with findings from other studies that reflect a positive outlook on AI's potential [10, 12]. The summary of findings is contained in Fig. 6.

Limitations

The sample size and sample distribution are limitations of this study. The relatively small sample size for both the interviews and the survey limits the generalizability of the conclusions generated. Despite this limitation, the focused nature of the sample allows for an in-depth exploration of perspectives and insights from a diverse range of healthcare professionals involved in cardiovascular care, providing rich qualitative data and nuanced perspectives on the challenges and opportunities associated with the integration of AI solutions in this context. Additionally, our survey sample composition presents a skew, with the majority of respondents being doctors. This overrepresentation of one group might introduce bias and limit the perspectives of other healthcare professionals. While the over-representation of doctors might introduce bias, it positions the study to capture in-depth insights from some of the primary users of cardiovascular AI technology. The geographical skew of participants toward Europe potentially limits the global applicability of the research conclusions.

Another critical limitation is the lack of focus on the accessibility and affordability of AI tools in low- and middle-income countries. While this study provides valuable insights into the challenges of AI integration in cardiovascular care, it primarily reflects perspectives from higher-income regions where access to advanced AI technologies is more feasible. Given that nearly 80% of the deaths from CVD occurred in low- and middle-income countries [1], the inability of these regions to access affordable AI tools might represent a significant barrier to the global adoption of AI in cardiovascular care. Future research should address this disparity, focusing on strategies to make AI technologies more accessible and affordable in resource-limited settings to ensure equitable advancements in cardiovascular health outcomes worldwide.

These limitations highlight the need for a cautious interpretation of the study's results and suggest the opportunity for extensive research to expand upon the findings.

Conclusion

In conclusion, this mixed-methods study provides valuable insights into the challenges of AI solutions in cardiovascular care. Interviews and surveys with a diverse group of healthcare professionals revealed key gaps in several areas: data-related issues, regulatory concerns, transparency, acceptance, change management, knowledge, and infrastructure. These findings emphasize the complexity and multifaceted nature of implementing AI in cardiovascular settings. Future research should focus on developing tailored approaches to address the identified challenges.

Overall, this study contributes to the growing body of literature on AI in healthcare by providing nuanced insights into the complexities of integrating AI solutions in cardiovascular care. By addressing these challenges and leveraging the opportunities presented by AI, we can strive towards more effective and personalized approaches to the diagnosis, management, and treatment of cardiovascular diseases, ultimately improving patient outcomes and advancing the field of cardiovascular medicine.

Supplementary Information

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Supplementary Material 1.

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Authors' contributions

VI: conceptualization, methodology, interview and survey design, data processing, visualization, analysis, and writing the main manuscript.

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Data availability

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Informed consent was obtained from all participants involved in the study. The research adhered to relevant guidelines and regulations, including those governing research practices at Deggendorf Institute of Technology. Since the study did not involve interventions requiring additional ethics approval under German law (Arzneimittelgesetz, AMG), as specified by the Joint Ethics Commission of the Universities of Bavaria (GEHBa) in their document'Häufig gestellte Fragen zum Ethikantrag,' and the WMA Declaration of Helsinki's'Ethical Principles for Medical Research Involving Human Subjects,' such approval was not sought.

Consent for publication

Not Applicable.

Competing interests

The authors declare no competing interests.

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