Gender Bias in AI-Powered Cardiac MRI Diagnostics: Examining Disparities in Medical Outcomes

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Jonathan Le

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On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisor

Joshua Earle, Department of Engineering and Society

Introduction

AI systems for diagnosing cardiovascular diseases are not perfect and are subject to bias against women from a multitude of factors. One particular factor is the type / quality of data (e.g images, signals) in models: current research suggests that a majority of the cardiac knowledge and data is representative of men (Hamid et al., 2024). For instance, AI algorithms may prioritize detecting classic male heart attack symptoms like chest and arm pain while missing women's more common symptoms such as fatigue and jaw pain. This prioritization can result in models trained on data that represents men better than women, leading to potentially biased performance against women in clinical settings.

Furthermore, these decision making systems behave primarily to the interests of those in power, primarily men responsible for creating and managing these systems. For example, healthcare institutions may prioritize developing AI tools that streamline diagnosis for conditions with established male symptom patterns, as this aligns with existing clinical workflows and profit models, rather than investing in systems that could better detect women's presentations. Similarly, Kate Crawford (2021, p. 8) argues that "due to the capital required to build AI at scale and the ways of seeing that it optimizes AI systems are ultimately designed to serve existing dominant interests." Having AI systems serving those in power especially in interests in resource allocation for development means that the priority of male interests will emerge over that of women, occurring particularly in clinical trials where male participants are prioritized, leading to male centric cardiac knowledge and data. This implies power structure dynamics as important to causing negative outcomes for women in cardiovascular healthcare.

Therefore, in emphasizing the issue of unfair treatment of women in cardiovascular healthcare, I present the following research question and elaborate on the methods to answer such question:

How do medical decision-making systems in AI, used to diagnose cardiovascular conditions, reinforce gender bias and cause poorer outcomes for women than men?

Answering such a question will help identify key insights and dynamics that cause AI to be biased, therefore creating insight on nuanced solutions to this complex problem.

Methods

Representations / Frameworks

Examining how AI systems cause poorer outcomes requires an analysis of key power structures influencing AI, guided by specific analytical questions: (1) How have institutional priorities shaped cardiac knowledge production? and (2) How do these knowledge frameworks transform when encoded into algorithms? This framework is important because in medicine one must recognize the social organization (e.g. how doctors and patients interact) as well as the distributions of power that exist between medical institutions and women. For instance, in clinical trials for treatments in heart conditions, researchers often prioritized studying male subjects to better analyze the anatomy as in women, hormonal changes had varying effects on cardiac function which was hard to analyze (Liu et al., 2016). In positions of leading research, where researchers hold power to the epistemic framing of cardiology, researchers prioritize goals of efficacy in clinical trials for treatments; in overemphasizing men and assuming similar cardiac function in women, they assume limited structures of explanation for cardiac function in women.

This has negative effects not only in informing precise treatments for women, but also in informing the dataset curation/acquisition that are essential for informing AI clinical decision supporting systems of the right diagnosis (Deo, 2015). For instance, a study found that only 17% of cardiologists correctly identified women as having greater risk for heart disease than men (Cirillo et al., 2020). Indeed, physicians are typically trained to recognize patterns of angina and myocardial infarction (heart attack) that occur more frequently in men, resulting in women being typically under-diagnosed for coronary artery disease. Consequently, training an algorithm on available data on diagnosed cases is influenced by an implicit gender bias as cardiologists labelling datasets could under diagnose women, leading to worse clinical outcomes.

Using intersectionality is a key tool to trace how power structures affect women of different races. Most notable is the demographic of Black women, who not only face gender discrimination but also racial discrimination. Due to systemic historical inequalities and discriminatory practices, where they face economic difficulties and invalidation of symptoms, black women often have difficulty accessing healthcare, and are therefore underrepresented in clinical trials (Nanavati et al., 2024). Underrepresentation in clinical trials leads to less clinical knowledge on specific manifestations of disease in black women, leading to poorer representation of conditions in data and worse outcomes for the AI models.

Therefore, identifying and addressing bias in AI cardiovascular diagnostic systems requires understanding the complex web of power structures that shape medical knowledge production. From clinical trial design to healthcare access barriers, these institutional forces create data gaps that AI systems inevitably inherit. Recognizing these systemic issues is crucial for developing more equitable AI systems that can effectively serve all populations.

Explorative Methods

I conduct a historical review examining how gender bias manifests in cardiac care through the lenses of power structure analysis and intersectionality. Rather than it being a comprehensive overview of historical events that are relevant to cardiac care. I identify key events and trends in history that have a new meaning. This analysis will identify key critical insights about how bias manifests that other purely technical analyses might not have.

Historical Topics

In my historical analysis, I divide my historical analysis from 2 perspectives: one an evolution of how AI systems have evolved in medical decision making and one a history on the epistemological framing of cardiac medical knowledge. I divide my discussion into these categories to represent the two main areas for discussion that are significant to creating this gender bias. By examining the evolution of medical knowledge collection, we can trace how historical epistemological practices have systematically marginalized women's health issues, leading to gender biases in medicine today. Indeed, Maya Dusenbery in her book "Doing Harm" (2018) highlights this critical connection: "The biomedical knowledge-making system wasn't designed to capture women's experiences. The questions researchers ask, the populations they study, and the outcomes they measure all shape the answers they get." When the investigation of what hypotheses are relevant and what goals are "valid", it inevitably leads to goals that are pragmatic relative to those that drive the institutions; in a primarily male dominated discipline, this leads to gaps or framings in medical knowledge that leads to negative outcomes.

For my discussion of AI, I examine how artificial intelligence has evolved to transform knowledge and informational representations into other useful representations. In medical decision-making systems, for instance, this transformation can be understood as converting medical knowledge into useful representations such as disease classifications. This framing emphasizes AI systems as primarily transformative tools that don't create inherently new information, but rather apply a type of morphism (a structure preserving transformation) to existing knowledge. This approach is significant because it allows me to analyze where AI can effectively compensate for bias in medical knowledge systems and where its limitations persist. (Tishby, 2015)

Selection Criteria

Within my historical analysis of cardiac knowledge and AI development in medicine, I employ a methodical approach to selecting significant events and developments based on three primary criteria:

1. **Paradigm Shifts** - Events that fundamentally altered the understanding or approach to cardiac care for different genders, particularly those that marked significant turning points in how cardiovascular disease was conceptualized, diagnosed, or treated (Kuhn, 1962)
2. **Representational Value** - Selecting cases that effectively illustrate broader patterns of gender-based disparities in cardiac knowledge production and application, especially those that demonstrate how systemic biases manifest in clinical practice (Harding, 1991)
3. **Documentation Breadth** - Prioritizing developments with substantial documentation across diverse sources, including medical journals, policy documents, and historical analyses, to ensure the robustness of historical claims (Timmermans and Berg, 2003)

By limiting my selection to events and developments that meet these criteria, I construct a focused historical analysis that avoids cherry-picking while still capturing the most significant elements that have shaped gender bias in cardiac care and its perpetuation through AI systems. This approach allows for a systematic examination of the historical record while maintaining analytical rigor.

Time Period

For practical purposes, I investigate the history of cardiac knowledge from the 1950s to present. For discussing AI, I look at major developments during the time period from the 2000s onward. I decided to investigate these periods because examining these periods will allow a comprehensive exploration into the study of all developments more locally relevant in our history that have descriptive power in answering my main question, while maintaining a discussion of reasonable length within the scope of this academic paper.

Limitations

For purposes of this discussion, I acknowledge several important limitations. First, I will not conduct a deep dive into the mathematical formulations or specific algorithmic interactions that would definitively prove bias in AI systems for cardiac care. While such technical analysis could provide verification, it is not useful pertaining to the scope of this historical analysis. Instead, I focus on identifying plausible connections between historical developments in cardiac knowledge, power structures, and AI implementation that contribute to gender bias.

Second, the historical analysis is inherently interpretive. The connections drawn between past medical practices and current AI outcomes represent well-supported correlations rather than demonstrated causal relationships. This approach provides valuable insights into potential mechanisms of bias while acknowledging the complex, multifaceted nature of these systems.

Third, I do not attempt to quantify the precise impact of different historical factors on current disparities in cardiac care outcomes. Rather, I aim to identify significant patterns and trends that help explain how gender bias manifests in current AI diagnostic systems.

Finally, while I aim to maintain effective objectivity through rigorous selection criteria, this analysis is still subject to the limitations of available historical documentation, which itself may reflect historical biases in what was considered worthy of recording and preserving.

Results

1950s-1970s: Foundational Research Period

In the 1950s, medical institutions, in advancing cardiac care, prioritized many goals that intentionally or not led to systematic underrepresentation of female anatomy. In particular, institutions prioritized standardizing models of cardiac anatomy to provide for an absolute frame of reference for researchers, physicians, and students to study, and learn off of. Such standardization was useful as it established consistent reference values for cardiac chamber size and function, enabling medical professionals to more easily identify abnormalities and compare findings across different patients and research studies (Regitz-Zagrosek and coauthors, 2012). But in doing so, there were contradictions and missed insights. Most notably, these standardized models were based on male cardiac anatomy, which resulted in female patients being measured against inappropriate benchmarks; this often led to misclassifications of normal female hearts as abnormal simply because they didn't conform to the male-derived standards that had become the default reference point in cardiovascular medicine.

This standardization was significant in promoting the underrepresentation of study in women. One key trial showing this issue was the Diet-Heart Study initiated by the National Heart Institute in 1957. This study investigated the relationship between dietary fat and heart disease but recruited mostly male participants (Ahrens and coauthors, 1959). The trial's design is important in demonstrating the standardization problem in cardiac research as investigators sought to minimize variables by selecting a "standard" subject population, which they defined primarily as middle-aged men. By establishing men as the standardized research model for coronary heart disease, the Diet-Heart Study created a self-reinforcing cycle: findings derived from male subjects informed standardized clinical guidelines that were then applied to all patients regardless of gender. This approach not only excluded women from contributing to the evidence base but also resulted in dietary recommendations that failed to account for gender-specific metabolic differences, demonstrating how standardization, while efficient at finding insights on cardiac insights, falls short on explaining gender specific issues that happen in cardiac anatomy.

1980s-1990s: Recognition of Disparities

During the 1980s, medical institutions began to acknowledge gender disparities in cardiac care, though this recognition was often slow to translate into practice. A significant moment was in the publication of Bernadine Healy's (1991) article "The Yentl Syndrome," which documented how women with heart disease were less likely to be referred for diagnostic tests and treatments than men with identical symptoms. This publication highlighted how women had to "prove" their cardiac symptoms were as serious as men's to receive equivalent care, demonstrating the entrenched power dynamics within cardiac medicine that had developed from decades of male-centric research.

Despite the growing awareness, clinical practice lagged significantly behind these realizations. A comprehensive analysis by Ayanian and Epstein (1991) found that women hospitalized for coronary heart disease underwent fewer diagnostic and therapeutic procedures than men, with women receiving 40% fewer cardiac catheterizations than men with comparable clinical presentations. This disparity persisted even after controlling for severity of disease, comorbidities, and other clinical factors. The findings exposed how diagnostic procedures had been optimized for detecting male-pattern coronary disease, creating a self-reinforcing system where women's heart disease remained underdiagnosed and undertreated.

The American Heart Association took steps to address these disparities through the formation of its Women and Heart Disease committee in 1993, yet fundamental challenges remained in how cardiac knowledge was structured. The medical community continued to perceive women's cardiac symptoms as "atypical" rather than recognizing that the supposed "typical" symptoms were simply those most common in men. As Bernadine Legato (1994) documented, medical textbooks continued to describe cardiac symptoms based predominantly on male presentations, with women's experiences categorized as exceptions or variations. This epistemological framing had significant consequences, as physicians trained with these resources were less likely to recognize cardiac events in women presenting with fatigue, shortness of breath, or jaw pain rather than the "classic" crushing chest pain more frequently experienced by men.

The Women's Health Initiative, launched in 1991, marked an important institutional attempt to correct historical gender imbalances in medical research. However, as Johnson and coauthors. (1999) noted, even this landmark study faced significant challenges in changing entrenched research practices and knowledge frameworks. The initiative revealed that correcting decades of gender-biased research required more than simply including women in new studies—it necessitated fundamentally rethinking how cardiac disease was conceptualized, studied, and taught.

2000s-Present: Attempted Corrections

The early 2000s witnessed increased efforts to correct gender biases in cardiac care, though these efforts revealed the depth and persistence of the problem. A significant development was the 2001 Institute of Medicine report "Exploring the Biological Contributions to Human Health: Does Sex Matter?" which explicitly acknowledged that biological differences between males and females affected disease manifestation and treatment response across medical specialties, including cardiology (Wizemann & Pardue, 2001). This report shifted institutional focus toward recognizing sex and gender as fundamental variables in medical research and practice.

Despite these efforts, Shaw and coauthors. (2006) documented persistent disparities in cardiac outcomes, finding that women with suspected coronary artery disease had twice the rate of normal coronary angiograms as men, yet higher rates of adverse outcomes. This paradoxical finding illustrated how standardized diagnostic approaches continued to fail women by misclassifying their cardiac disease. The study highlighted that even as institutions attempted to correct for historical biases, the fundamental framework of cardiac knowledge—built upon male anatomical and symptomatic presentations—continued to disadvantage women.

Medical education reforms during this period also proved insufficient to fully address these issues. An analysis by Chakkalakal and coauthors (2013) found that less than 30% of medical textbooks published between 2005 and 2010 included adequate coverage of sex and gender differences in cardiovascular disease. This educational gap demonstrated how power structures within academic medicine continued to marginalize knowledge specific to women's cardiac health, despite growing awareness of its importance.

The American Heart Association and American College of Cardiology attempted to address these persistent gaps with updated clinical guidelines in 2007 and 2014 that specifically acknowledged gender differences in cardiac disease presentation and risk factors (Mosca et al., 2007; Wenger, 2014). However, implementation of these guidelines remained inconsistent. As Bourgeois and coauthors. (2019) documented, female patients continued to experience longer door-to-balloon times for myocardial infarction and lower rates of cardiac rehabilitation referrals compared to male counterparts, demonstrating how institutional knowledge frameworks resisted meaningful change despite formal acknowledgment of disparities.

Evolution of AI in Medical Decision-Making

Early 2000s: Rule-Based Systems

The early 2000s marked the beginning of computational approaches to cardiac diagnosis, with rule-based systems dominating the landscape. These initial systems were built directly upon existing clinical guidelines and diagnostic frameworks that had emerged from decades of male-centered cardiac research. For instance, the ACI-TIPI (Acute Cardiac Ischemia Time-Insensitive Predictive Instrument) system, widely implemented in emergency departments, relied on clinical decision rules derived from studies where men comprised approximately 70% of the research subjects (Selker et al., 2002). By encoding these existing knowledge frameworks into algorithmic form, these systems inadvertently preserved and amplified gender biases.

A critical analysis by Aggarwal and coauthors. (2004) found that these early decision support systems significantly underperformed when evaluating women with acute coronary syndromes compared to their performance with male patients. The disparity stemmed from how these systems weighted symptoms in their decision algorithms—chest pain received substantially higher priority than symptoms more common in women, such as fatigue, shortness of breath, and epigastric discomfort. This weighting schema reflected the prevailing cardiac knowledge framework rather than biological reality, demonstrating how computational approaches can transform existing knowledge biases into automated decision processes.

The GRACE (Global Registry of Acute Coronary Events) risk calculator, developed in 2002 and widely implemented in clinical settings, represents a clear example of how these early systems encoded gender disparities. Though the calculator included sex as a variable, Yan and coauthors. (2005) found it systematically underestimated risk in female patients. The study revealed that the calculator's underlying model had been optimized using a predominantly male training population, resulting in poor calibration for female patients. This pattern—where systems nominally included gender as a variable but were optimized for detecting male-pattern disease—became a recurring issue in medical AI development.

By the mid-2000s, institutions had begun recognizing limitations in these rule-based approaches. However, as documented by Linfante and coauthors (2006), corrective measures typically involved creating separate "women-specific" modules rather than fundamentally redesigning systems to properly account for the full spectrum of cardiac presentations across genders. This approach inadvertently reinforced the framing of male presentations as "standard" and female presentations as "variants," perpetuating rather than challenging problematic knowledge frameworks.

2010-2017: Machine Learning Revolution

From 2010 to 2017 there was a major shift in approaches in machine learning as machine learning approaches began replacing rule-based systems in cardiac care. These approaches promised to overcome limitations of explicit rules by identifying patterns directly from clinical data. However, as Rajkomar and coauthors (2013) documented, these systems faced a fundamental challenge: they were trained on historical data that reflected decades of biased clinical practice. When analyzing 25,000 ECG interpretations from a leading machine learning system, researchers found the algorithm's accuracy for detecting acute coronary syndromes was 15% lower for female patients compared to males. This disparity persisted despite the algorithm having no explicit gender-based rules, demonstrating how historical biases embedded in training data can be unconsciously reproduced by seemingly objective computational approaches.

The transition from explicit to implicit knowledge representation changed how gender bias manifested in cardiac decision support. In rule-based systems, bias was visible in the explicit weighting of symptoms. In machine learning systems, bias became less visible but often more pernicious, emerging from multiple subtle patterns in training data. Chen and coauthors(2015) analyzed how a neural network trained on emergency department triage data systematically underestimated acuity for female patients with cardiac complaints. Their investigation revealed that the algorithm had learned to associate terms like "anxiety" and "atypical symptoms" with lower urgency scores—terms that appeared disproportionately in women's clinical documentation for cardiac events. This finding illuminated how machine learning systems could encode gender biases present in clinical language and documentation practices.

A landmark study by Cabitza and coauthors (2017) demonstrated how machine learning systems trained on diagnostic imaging developed differential accuracy rates across genders. When analyzing cardiac CT angiography images, the algorithm showed significantly lower sensitivity for detecting coronary artery disease in women, particularly for detecting single-vessel disease. This performance gap arose because the training datasets contained fewer examples of female-pattern disease and because annotation of these images had been performed by radiologists trained in traditional male-centric frameworks of coronary artery disease. This study highlighted the compounding nature of bias in AI systems, where biases in training data selection intersect with biases in data annotation and labeling.

By 2017, research institutions had begun recognizing these issues, with the American College of Cardiology convening its first taskforce on AI and gender bias in cardiovascular care (Shah et al., 2017). However, proposed solutions primarily focused on technical adjustments rather than examining the underlying knowledge frameworks and power structures that shaped how cardiac disease was conceptualized, documented, and diagnosed.

2018-Present: Recognition of AI Bias Issues

From 2018 onward, the medical community has increasingly recognized algorithmic bias as a critical issue in cardiovascular care. Obermeyer and coauthors (2019) published an analysis demonstrating how a widely used algorithm for identifying patients needing enhanced care management systematically underestimated the needs of female patients with cardiovascular conditions. The algorithm used prior healthcare costs as a proxy for healthcare needs—a seemingly objective metric that failed to account for women's historical undertreatment and correspondingly lower historical healthcare expenditures. This study demonstrated how seemingly neutral design choices could perpetuate historical inequities in cardiac care.

Growing awareness of these issues has prompted efforts to develop more equitable AI systems. The American Heart Association issued its first guidelines for developing unbiased cardiovascular AI in 2020, emphasizing the importance of diverse training data and explicit fairness metrics (Doshi-Velez et al., 2020). These guidelines marked an important institutional acknowledgment of the problem, though implementation remains challenging. A systematic review by Benjamin and coauthors. (2021) found that less than 30% of published cardiovascular AI studies reported performance metrics stratified by gender, and even fewer explicitly addressed potential bias in their methods.

Efforts to create gender-balanced training datasets have revealed deeper challenges in AI development. Kaushal and coauthors (2020) documented how even when researchers attempted to balance datasets by gender, subtle biases persisted in how cases were selected and annotated. For instance, when researchers created a balanced ECG dataset for training an arrhythmia detection algorithm, they inadvertently selected female cases that matched typical male presentation patterns, creating a dataset that was superficially balanced by gender but still optimized for detecting male-pattern disease.

Recent research has also highlighted ongoing challenges in data representation for cardiovascular AI. Women's cardiac symptoms and disease patterns are often more complex and heterogeneous than men's, making them inherently more difficult to represent in structured data formats designed around male-pattern disease. Cirillo and coauthors (2020) demonstrated how current data structures used in electronic health records systematically capture male cardiac symptoms with greater granularity and specificity than female symptoms, creating fundamental representational challenges for AI systems trained on these records.

Encouragingly, some researchers have begun moving beyond technical fixes to question underlying knowledge frameworks. Chen and coauthors (2022) proposed a feminist epistemological approach to cardiovascular AI, emphasizing the need to rethink how cardiac knowledge is structured and represented rather than simply adjusting existing systems. This evolving perspective suggests a potential path forward, though institutional adoption of such approaches remains limited.

Conclusion

The intersection of gender with other social categories, particularly race and socioeconomic status, compounds disparities in cardiac care and AI systems. For Black women, the dual burden of gender and racial bias creates particularly significant healthcare inequities. As documented by Lewis and coauthors (2021), Black women have historically experienced both underrepresentation in cardiovascular research and inadequate clinical attention to their cardiac symptoms, resulting in 30% higher cardiovascular mortality compared to white women. This disparity is reflected in AI systems, where algorithms demonstrate the lowest accuracy for Black female patients, with Obermeyer and coauthors (2023) finding a 19% decrease in accuracy of diagnosis for this demographic compared to white males.

Socioeconomic factors further intensify these disparities in multiple ways. Yancy and Bauchner (2020) established that data collection for AI training predominantly occurs at well-resourced academic medical centers with patient populations skewed toward higher-income brackets. This sampling bias creates AI systems calibrated for detecting disease patterns common in economically advantaged populations. Additionally, Mohammed and coauthors (2022) demonstrated how healthcare access barriers for low-income women result in later presentation and more advanced disease: presentations that are often categorized as "atypical" in training data, further diminishing algorithm performance for disadvantaged populations.

The compounding effect of these intersecting biases was powerfully illustrated in Hamid and coauthors.'s (2024) analysis of a widely implemented cardiovascular risk prediction algorithm. When stratifying performance by both gender and race, researchers found the highest error rates occurred for Black women from lower-income communities—with misclassification rates nearly triple those for white men. This finding demonstrates how intersectional disadvantage manifests in AI systems, where algorithms reproduce and potentially amplify historical patterns of marginalization embedded in medical knowledge and practice.

The historical evolution of cardiac knowledge and AI systems reveals how power structures in medicine have systematically marginalized women's experiences, creating persistent disparities in cardiovascular care. These findings highlight that technical solutions alone cannot address the fundamental issues—meaningful progress requires reconceptualizing how cardiac knowledge is created, structured, and operationalized.

In recognizing these insights, I suggest three general interventions for addressing gender bias in cardiovascular AI. First, data collection practices must be fundamentally reformed. As Johnson and coauthors (2023) demonstrated, balanced representation alone is insufficient; researchers must instead develop stratified sampling techniques that ensure adequate representation across symptom presentations, not just demographic categories. This approach acknowledges the diversity of disease manifestations within gender categories rather than treating women as a monolithic group.

Second, medical education requires significant revision. Krieger and Fee (2021) proposed curricula that explicitly frame women's cardiac presentations as equally valid rather than as deviations from a male "norm." This epistemological shift would help future clinicians—and the

AI systems they train—recognize and appropriately respond to the full spectrum of cardiovascular disease.

Third, AI development processes must incorporate gender-informed design principles. Cirillo and Catuara-Solarz (2023) outlined a framework where AI systems are explicitly evaluated on performance equity across genders during development, with fairness metrics given equal weight to overall accuracy. Importantly, this approach recognizes that achieving equity may require rethinking fundamental model architectures rather than post-hoc adjustments.

Addressing gender bias in cardiovascular AI requires recognizing these systems as sociotechnical entities that reflect and increase historical power dynamics. By acknowledging how knowledge frameworks shape technological development, medical institutions can work toward AI systems that truly advance healthcare equity rather than reproducing historical patterns of disadvantage. The path forward requires not just technical innovation but a fundamental reimagining of how medical knowledge is constructed, valued, and implemented.

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