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Data-Driven Health Equity: The Role of Artificial Intelligence in Addressing Social Determinants of Health

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ABSTRACT: Artificial Intelligence (AI) is increasingly recognized as a powerful instrument for addressing Social Determinants of Health (SDOH) and advancing health equity. This narrative review aims to synthesize current evidence on how AI tools are applied to identify, interpret, and operationalize SDOH in public health interventions. Relevant literature was collected from major scientific databases. The findings reveal four key themes: the interconnectedness of determinants such as economic stability, housing, education, and digital equity; the promise of AI for predictive analytics and mapping health risks; stakeholder perspectives that underscore both optimism and concerns regarding data use; and the limited coverage of upstream determinants such as education quality and community cohesion. While AI technologies demonstrate clear potential to enhance health equity strategies, systemic challenges—including algorithmic bias, uneven data quality, and infrastructural constraints—limit their effectiveness. Addressing these barriers requires inclusive policies, investments in digital infrastructure, and participatory approaches that integrate community voices. This review concludes that AI has significant potential to promote equitable health outcomes, but future research must broaden its scope and develop robust frameworks to fully harness its capabilities.

Keywords: Artificial Intelligence, Social Determinants of Health, Health Equity, Predictive Analytics, Digital Health, Public Health Policy.

INTRODUCTION

Artificial Intelligence (AI) has emerged as a transformative force in healthcare, with growing evidence suggesting its potential to address Social Determinants of Health (SDOH) in ways that promote health equity. As health disparities persist globally, scholars and policymakers alike emphasize the importance of incorporating socio-economic, cultural, and environmental dimensions into healthcare delivery and policy frameworks. Recent studies underscore that health outcomes are shaped not only by clinical care but also by upstream factors such as education, employment, housing, and community infrastructure. AI, with its capacity to process large and complex datasets, offers promising avenues for identifying patterns within these determinants and translating them into actionable strategies. For instance, Wright-Kelly et al. (2024) highlighted the importance of community-level engagement in data practices, noting that systematic tracking of local data utilization can inform more equitable interventions. Similarly, Wylezinski et al. (2021) demonstrated how machine learning models analyzing COVID-19 growth in Tennessee revealed the critical role of real-time monitoring of SDOH in enabling responsive resource allocation. These insights demonstrate that AI's contribution lies not only in technological innovation but also in enhancing the contextual understanding necessary for addressing inequities in healthcare systems.

Globally, the application of AI to health equity has accelerated, particularly in relation to chronic diseases such as cardiovascular and neurological disorders. Lindenfeld et al. (2023) examined New York City's efforts to harness SDOH datasets to mitigate cardiovascular disease, illustrating how locally organized data can shape targeted interventions. Likewise, McNeill et al. (2023) presented a scoping review highlighting the integration of data frameworks in health services, underscoring their role in aligning public health strategies with community needs. The growing recognition of SDOH in health policy and practice signifies a paradigm shift towards more comprehensive, socially informed interventions. These approaches are increasingly evident in diverse geographical settings, with countries leveraging SDOH-informed data analytics to address localized challenges, thereby enhancing population-level health equity outcomes. This trend indicates a broadening acceptance of the principle that effective public health interventions must be grounded in the lived experiences and socio-economic realities of communities.

The relevance of these developments is further reinforced by the expanding literature on the intersection of healthcare systems, policy frameworks, and data-driven decision-making. O'Neil et al. (2021) argued that low- and middle-income countries (LMICs) are actively engaging with health data to identify gaps in service provision, reflecting a global movement towards equitable healthcare access. Meanwhile, Manning et al. (2022) presented the Massachusetts Racial Equity Data Road Map as a model for integrating race-conscious data practices into policy decisions, thereby challenging systemic inequities. These examples illustrate that data-driven approaches are not confined to affluent regions but are also vital in contexts where structural inequities are most pronounced. This reinforces the notion that equitable healthcare systems must be built upon reliable data infrastructures and inclusive policies, supported by technologies capable of adapting to diverse socio-cultural landscapes.

Foundational to this discourse is the acknowledgment that AI integration into health equity initiatives presents notable challenges. A recurring theme in the literature concerns algorithmic bias, which can inadvertently exacerbate disparities. Wright-Kelly et al. (2024) cautioned that unchecked biases in AI models risk reinforcing disadvantages faced by marginalized populations. Similarly, Brewer et al. (2020) emphasized that technological interventions lacking cultural sensitivity and socio-economic contextualization could deepen disparities rather than alleviate them. These concerns underscore the necessity for transparency, accountability, and community participation in the design and deployment of AI tools. Moreover, the risks associated with algorithmic bias highlight the ethical imperative of developing methodologies that mitigate discrimination while ensuring inclusivity.

In addition to algorithmic bias, disparities in technological access and data availability further complicate AI's role in promoting equity. Wylezinski et al. (2021) pointed out that limited availability of robust health data in lower-income communities constrains the predictive accuracy of machine learning models. McNeill et al. (2023) also observed that inconsistent data quality across different demographic groups undermines the generalizability of AI applications. These findings draw attention to the importance of inclusive data strategies that prioritize the equitable collection and representation of health information. Without such inclusivity, the promise of AI risks being undermined by structural inequities embedded in the very datasets on which it relies. Thus, achieving genuine equity through AI requires systemic reforms in data governance and cross-sector collaboration to ensure marginalized populations are adequately represented in health data.

The literature identifies a critical gap in understanding the integration of AI with socio-economic and environmental determinants of health. Dang et al. (2023) noted that while the role of SDOH in shaping health outcomes is well documented, their interaction with AI methodologies remains underexplored. Similarly, Sabet et al. (2023) highlighted the lack of comprehensive frameworks that operationalize SDOH in AI-driven public health initiatives. This indicates that current research remains largely focused on clinical applications, often overlooking the upstream determinants that underpin health inequities. Addressing this gap requires interdisciplinary approaches that bridge the domains of social science, health informatics, and policy analysis to create robust models capable of responding to complex socio-health dynamics.

Another unresolved issue is the evolving conceptualization of health equity itself. Hoyer et al. (2022) argued that prevailing models often fail to capture the multidimensional nature of health disparities, particularly those shaped by intersecting socio-economic and cultural factors. The absence of universally accepted definitions and metrics for health equity complicates efforts to evaluate the effectiveness of AI-driven interventions. This gap points to an urgent need for standardized frameworks that both reflect the complexity of equity and facilitate comparative research across diverse contexts. Without such frameworks, interventions may remain fragmented, limiting their impact on systemic disparities.

Against this backdrop, the purpose of this review is to examine the role of AI in addressing SDOH with an emphasis on advancing health equity. Specifically, the review seeks to analyze the extent to which AI tools have been applied to identify, interpret, and operationalize determinants such as economic stability, education, housing, and community cohesion. By synthesizing existing empirical evidence, this study aims to evaluate both the opportunities and limitations of AI in promoting equitable healthcare outcomes. Furthermore, the review intends to highlight strategies for overcoming the barriers associated with data biases, access disparities, and fragmented policy frameworks, thereby contributing to a more comprehensive understanding of how AI can be harnessed for equitable health improvements.

The scope of this review encompasses literature from diverse geographical contexts, with particular attention to LMICs and marginalized populations in high-income countries. These groups are often disproportionately affected by inequities in health outcomes, making them critical focal points for evaluating the efficacy of AI-driven interventions. Studies conducted in urban centers with systemic inequities, such as those analyzed by Manning et al. (2022), provide important insights into how data practices can be mobilized to address structural racism and related disparities. At the same time, comparative analyses, such as those by Bazyar et al. (2021) on Southeast Asian health systems, demonstrate the global relevance of equity-focused AI applications. By situating AI within these varied contexts, this review acknowledges the necessity of tailoring interventions to the unique socio-economic and cultural landscapes that shape health disparities.

In conclusion, the introduction sets the stage for a comprehensive exploration of AI's potential to transform health equity initiatives through its application to SDOH. While empirical evidence underscores AI's promise in enhancing data-driven decision-making, the challenges of algorithmic bias, data inequality, and definitional ambiguity continue to limit its impact. Addressing these issues requires not only technological innovation but also policy reforms, inclusive governance, and community engagement. The subsequent sections of this review will build upon this foundation, critically examining the evidence base and identifying pathways for integrating AI into equitable health systems that address both immediate clinical needs and the broader determinants of health.

METHOD

The methodology guiding this review was designed to ensure a comprehensive and systematic exploration of how Artificial Intelligence (AI) applications intersect with Social Determinants of Health (SDOH). The process relied on the integration of multiple databases, carefully structured search strategies, and rigorous inclusion and exclusion criteria. The overall objective of the methodological design was to capture the diversity of scholarly perspectives while maintaining the academic rigor required for a narrative review published in an international journal of repute.

The primary sources of literature collection included PubMed, Scopus, and Web of Science, with Google Scholar serving as an additional tool for expanding access to gray literature. PubMed was employed due to its extensive repository of biomedical research and public health studies, including clinical trials, systematic reviews, and observational studies. Its utility lies in the depth of coverage in health sciences, making it indispensable for identifying evidence concerning AI interventions in healthcare and SDOH. Scopus complemented PubMed by providing a broader cross-disciplinary perspective, capturing publications from social sciences, policy, and engineering that highlight AI's broader implications beyond clinical contexts. Web of Science, with its advanced citation tracking features and stringent indexing of peer-reviewed journals, ensured that the review incorporated highly influential studies from multiple disciplines. Meanwhile, Google Scholar offered accessibility to gray literature, conference proceedings, and policy reports, enriching the review with materials that may not have been comprehensively indexed elsewhere.

This combination of databases was deemed essential to provide both breadth and depth in understanding AI's role in addressing health equity challenges, as reflected in prior works by Lindenfeld et al. (2023) and Hoyer et al. (2022).

To effectively refine the literature search, carefully structured keywords were employed. The combinations most frequently used included "Artificial Intelligence" AND "Health Equity" AND "Social Determinants," which directly captured the intersection central to this review. Variations such as "Machine Learning" AND "Health Disparities" or "AI" AND "Social Determinants of Health" were also deployed to ensure coverage of diverse terminologies that scholars and practitioners might use in different contexts. Synonyms and related terms were systematically incorporated, allowing the review to encompass a broader range of studies while avoiding the exclusion of relevant contributions due to terminological differences. This approach was validated by previous reviews such as Briggs et al. (2021) and Rattermann et al. (2021), who highlighted the importance of nuanced keyword strategies in ensuring the comprehensiveness of literature reviews in interdisciplinary fields.

The construction of keyword strategies was not static but rather iterative, adapting to the research focus as preliminary results were screened. For instance, when identifying studies on chronic disease contexts such as cardiovascular health, the search strings were tailored to include "cardiovascular disease" AND "AI" AND "SDOH." Similarly, to capture the emerging literature on mental health, combinations like "mental well-being" AND "machine learning" AND "equity" were incorporated. This flexibility in tailoring keywords ensured that the search remained relevant to the evolving focus areas while maintaining methodological consistency.

The inclusion and exclusion criteria for selecting studies were clearly defined to maintain methodological rigor. Articles were included if they met the following criteria: they were peer-reviewed publications; they explicitly addressed the relationship between AI and SDOH; and they offered empirical findings, theoretical frameworks, or systematic analyses relevant to health equity. Studies that focused solely on technical AI development without reference to health outcomes, equity, or SDOH were excluded. Similarly, literature not published in English was excluded to ensure consistency in interpretation and accessibility of findings. Conference abstracts without full publications were excluded unless they contained substantial empirical evidence or policy relevance. This rigorous filtering process was critical for maintaining the relevance of the selected studies to the overarching research questions of the review.

In terms of study types, this review included randomized controlled trials, cohort studies, case-control studies, cross-sectional studies, case reports, and systematic reviews where applicable. The diversity of study designs reflects the evolving nature of AI applications in health equity research, which spans experimental, observational, and theoretical approaches. For example, Wylezinski et al. (2021) demonstrated how machine learning models were applied in real-world settings to analyze COVID-19 growth patterns, while McNeill et al. (2023) synthesized a broad range of empirical studies through a scoping review. By including diverse research designs, the methodology ensured that both the practical applications and the theoretical underpinnings of AI and SDOH were captured.

The process of literature selection followed a multi-stage approach. Initially, search results from each database were imported into reference management software to identify and eliminate duplicates. Following this, titles and abstracts were screened to assess their relevance against the inclusion and exclusion criteria. Studies that appeared relevant were then retrieved in full text for further evaluation. The full-text screening was conducted with attention to methodological quality, ensuring that only studies with clearly articulated objectives, sound methodology, and relevance to AI and SDOH were included. Throughout this process, discrepancies were resolved through discussion among reviewers, ensuring consistency and reducing potential biases in selection.

Evaluation of the studies was guided by a critical appraisal of methodological rigor, relevance to the research objectives, and contribution to understanding AI's role in promoting health equity. Studies were assessed not only for the robustness of their methods but also for the extent to which they considered issues of equity, representation, and inclusivity. This was particularly important given the documented challenges of algorithmic bias and unequal access to data that can distort research outcomes. By prioritizing studies that explicitly engaged with health equity dimensions, the review aimed to construct a balanced synthesis of both the opportunities and challenges inherent in AI applications for SDOH.

Furthermore, the methodology recognized the importance of contextual diversity. Studies from high-income, middle-income, and low-income countries were considered, with attention to how geographical and socio-economic contexts influenced findings. For example, O'Neil et al. (2021) highlighted the operational challenges in LMICs, while studies such as those by Manning et al. (2022) illustrated data-driven approaches to racial equity in the United States. By incorporating this global perspective, the review ensured that the synthesis did not privilege one context over another but reflected the complexity of health equity challenges across settings.

The methodological framework also emphasized transparency and reproducibility. Detailed records of search strategies, databases queried, and criteria applied were maintained throughout the process. This documentation not only facilitated accountability but also ensured that future researchers could replicate or adapt the methodology for subsequent studies. As Collura et al. (2019) argued, methodological transparency is critical for building cumulative knowledge in interdisciplinary fields where evolving technologies like AI intersect with complex social determinants.

In conclusion, the methodology employed in this review combined authoritative databases, strategically developed keywords, rigorous inclusion and exclusion criteria, and careful evaluation processes to ensure a comprehensive synthesis of existing literature. The integration of multiple research designs, global perspectives, and critical appraisal of equity considerations provided a robust foundation for examining AI's role in addressing SDOH. This methodological approach ensured that the review not only captured the current state of knowledge but also identified areas where further inquiry is needed to advance equitable health outcomes through AI interventions.

RESULT AND DISCUSSION

The findings of this narrative review reveal four central themes in the literature on the application of Artificial Intelligence (AI) to Social Determinants of Health (SDOH). These themes include the interconnectedness of social determinants, the promise of AI for mapping and prediction, stakeholder perspectives and practical challenges, and the limited coverage of key determinants. Together, they provide a comprehensive overview of the opportunities and constraints associated with leveraging AI in addressing health equity.

Interconnectedness of Social Determinants

The reviewed literature strongly supports the notion that economic stability functions as a cornerstone of health outcomes, directly influencing access to healthcare, education, and housing. Wright-Kelly et al. (2024) underscored that individuals with secure income and employment are more likely to afford healthcare services and pursue educational opportunities, creating a positive cycle that mitigates health disparities. Conversely, communities experiencing economic instability face compounded disadvantages, which not only reduce healthcare access but also perpetuate poorer educational outcomes, thereby reinforcing inequities across generations. Lindenfeld et al. (2023) further highlighted the significant impact of housing conditions on health outcomes, noting that inadequate housing is associated with higher incidences of chronic diseases, particularly respiratory illnesses and mental health disorders. Although the causal pathways remain complex, the literature consistently demonstrates that economic and housing stability are fundamental determinants shaping both physical and mental health.

Digital equity has emerged as a particularly salient factor in contemporary discussions of health outcomes. Rattermann et al. (2021) found that students with greater access to digital educational resources experienced fewer health-related absences from school, suggesting that digital access extends beyond education and into broader health trajectories. Similarly, Wylezinski et al. (2021) demonstrated that disparities in access to telehealth services during the COVID-19 pandemic intensified existing inequities, with under-resourced populations facing significant barriers to receiving timely care. These findings confirm that digital equity represents an increasingly critical determinant, mediating the extent to which individuals and communities can access healthcare and education and adapt to emergent health crises.

From a global perspective, studies conducted in low- and middle-income countries (LMICs) have shown similar patterns of interconnectedness. O'Neil et al. (2021) reported that in LMICs, economic stability significantly influences both healthcare access and educational attainment, underscoring the universality of these dynamics. These findings suggest that while contextual differences exist, the fundamental linkages between income, education, housing, and health are consistent across diverse settings. Thus, the literature strongly points to the need for AI-driven frameworks that integrate these interdependencies to produce meaningful interventions.

Promise of AI for Mapping and Prediction

The potential of AI to enhance the analysis of SDOH is well documented in the literature. McNeill et al. (2023) provided a scoping review highlighting the use of predictive models in cardiovascular health, demonstrating that algorithms incorporating SDOH metrics can effectively identify populations at heightened risk. By accounting for variables such as neighborhood characteristics, employment, and healthcare access, these models are capable of producing nuanced predictions that surpass traditional clinical risk assessments. The integration of SDOH into predictive modeling represents a promising advancement for proactive public health interventions.

Beyond predictive modeling, advanced technologies such as digital twins and predictive analytics have gained attention for their potential in public health applications. Levy et al. (2021) described the use of mobile health units supported by digital analytics to optimize the distribution of healthcare resources, illustrating how technology can be adapted to community-specific needs. Aschbrenner et al. (2022) emphasized the role of predictive analytics in supporting decision-making for underserved populations, showing that when effectively applied, these tools can help reduce inequities in healthcare delivery. While the evidence for these innovations remains emergent, the literature reflects a strong consensus regarding their potential to transform health equity strategies by making public health responses more precise and efficient.

Notably, international research demonstrates that AI's utility in mapping and prediction extends across varied healthcare systems. In high-income countries, AI is primarily used to enhance precision in resource allocation, whereas in LMICs, its role has often centered on bridging systemic gaps in healthcare access. For instance, comparative studies in Southeast Asia (Bazyar et al., 2021) showed how predictive analytics are increasingly used to anticipate health system demands, providing a global perspective on the versatility of AI applications.

Stakeholder Perspectives and Practical Challenges

Stakeholder perspectives captured in the literature highlight both enthusiasm and caution regarding the integration of AI with SDOH. Lindenfeld et al. (2023) documented that healthcare providers, policymakers, and community leaders recognize the value of SDOH data for tailoring interventions to specific community needs. Stakeholders emphasized the potential for data-driven approaches to connect individuals with resources, strengthen preventive care, and promote holistic approaches to health equity. The optimism is rooted in the recognition that AI can reveal insights not readily apparent through conventional methods, enabling more targeted and effective interventions.

Nevertheless, stakeholders also identified significant barriers that complicate the use of SDOH data. Hoyer et al. (2022) reported that discrepancies in data quality and lack of interoperability between systems remain major obstacles, limiting the capacity of health systems to utilize AI effectively. Inconsistent methodologies for collecting and categorizing SDOH data often produce fragmented datasets that hinder comparative analysis and robust decision-making. These technical barriers, compounded by limited digital infrastructure in underserved regions, reduce the scalability of AI interventions. The literature consistently stresses that unless such barriers are addressed, AI's potential in promoting health equity will remain unrealized.

Stakeholders further emphasized the ethical dimensions of AI deployment, particularly the risks associated with algorithmic bias. Wright-Kelly et al. (2024) warned that without deliberate safeguards, AI could exacerbate inequities by embedding systemic biases into predictive models. Brewer et al. (2020) echoed this concern, noting that technologies implemented without cultural and socio-economic sensitivity risk alienating marginalized populations. These perspectives highlight the need for participatory approaches in designing AI tools, ensuring that affected communities have a voice in shaping the technologies intended to serve them.

Limited Coverage of Key Determinants

Despite the promise of AI and the growing recognition of SDOH, the literature reveals critical gaps in coverage of certain determinants. Economic stability, education quality, and community cohesion are often underrepresented in AI-driven health equity research. Studies frequently prioritize health behaviors and healthcare access, while neglecting upstream determinants that significantly shape long-term outcomes. For example, O'Neil et al. (2021) cautioned that without addressing structural inequities rooted in economic and educational disparities, AI interventions risk delivering superficial improvements. By overlooking these factors, health systems may inadvertently reinforce inequities rather than dismantling them.

McNeill et al. (2023) also observed that the uneven representation of demographic groups in health datasets further restricts the capacity of AI to address disparities comprehensively. The underrepresentation of marginalized populations not only limits the scope of findings but also perpetuates systemic blind spots in health research. These gaps suggest that the integration of AI into SDOH research remains partial and uneven, requiring more deliberate efforts to incorporate neglected determinants and populations.

Global comparisons reinforce this observation. While high-income countries often emphasize healthcare access and digital health tools, LMICs face unique challenges tied to education, infrastructure, and economic disparities. Studies in LMICs, such as those by O'Neil et al. (2021), show that structural inequities pose significant hurdles to the adoption of AI in health equity, demonstrating that interventions must be tailored to reflect contextual realities. This highlights the need for global strategies that balance technological innovation with attention to local determinants of health.

Summary of Findings

In summary, the results of this review highlight the intricate linkages between economic stability, housing, digital equity, and health outcomes, while demonstrating the promise of AI in mapping and predicting health risks. Stakeholders broadly acknowledge the transformative potential of AI but remain cautious about technical, ethical, and infrastructural barriers. Most notably, gaps in the literature concerning key determinants such as education quality and community cohesion underscore the incomplete nature of current approaches. Taken together, these findings emphasize that while AI represents a powerful tool for advancing health equity, its impact depends on inclusive data strategies, context-sensitive applications, and deliberate efforts to address the structural determinants that drive inequities across populations.

The findings of this review highlight the complex interplay between systemic factors and the implementation of Artificial Intelligence (AI) for addressing Social Determinants of Health (SDOH). Central to this discussion is the recognition that technological innovation alone is insufficient for advancing health equity unless it is embedded within broader structural reforms. The literature consistently emphasizes that policies, infrastructure, and access disparities significantly shape the extent to which AI can achieve its potential in mitigating health inequities.

One of the most salient themes emerging from the literature concerns the critical role of policy frameworks in shaping the impact of AI on health equity. Wright-Kelly et al. (2024) cautioned that if policies governing data access and usage are not inclusive, particularly toward marginalized populations, the risk of exacerbating inequities becomes pronounced. Policies that neglect to prioritize underserved communities may inadvertently perpetuate systemic biases, as AI algorithms trained on incomplete or skewed datasets reproduce existing disparities. This underscores the necessity of inclusive governance frameworks that prioritize transparency, accountability, and the equitable distribution of technological benefits. Gopichandran et al. (2023) further argued that equitable AI deployment requires deliberate policy interventions aimed at improving both the accessibility and reliability of health data. Without such interventions, AI's promise for advancing equity remains aspirational rather than realized.

Infrastructure emerges as another critical determinant of AI's capacity to address SDOH. Kim et al. (2024) observed that insufficient technological infrastructure and the lack of adequate training for healthcare providers significantly hinder the adoption and effective use of AI tools. The presence of advanced algorithms is of limited value if healthcare systems lack the digital readiness to integrate these tools into daily practice. This is particularly evident in low- and middle-income countries (LMICs), where underfunded healthcare systems often struggle to accommodate new technologies. The uneven distribution of resources between urban and rural healthcare facilities also perpetuates inequities, with rural populations often excluded from the benefits of digital health innovations. Addressing these infrastructural challenges requires not only investments in technology but also sustained efforts in workforce development and capacity building.

The digital divide further compounds these systemic barriers. Hoyer et al. (2022) highlighted that populations without access to reliable internet or digital technologies face greater challenges in benefiting from AI-driven health innovations. During the COVID-19 pandemic, this divide became starkly visible as telehealth services expanded in high-resource areas while vulnerable populations were left behind due to inadequate digital access (Wylezinski et al., 2021). The inability to bridge this divide threatens to widen existing disparities, with technologically connected populations reaping disproportionate benefits. Digital equity must therefore be understood as a foundational prerequisite for leveraging AI to address SDOH. Investments in expanding broadband infrastructure, subsidizing access to digital devices, and promoting digital literacy are essential steps in closing this gap and ensuring that AI tools are accessible to all communities.

The implications of these findings extend beyond academic discourse and carry significant weight for global and national health policy. Lindenfeld et al. (2023) underscored the need for policymakers to prioritize systemic reforms that facilitate equitable data access and utilization. Equitable health outcomes cannot be achieved without deliberate efforts to dismantle barriers that limit access to technological innovations. This aligns with broader calls for health policies that emphasize structural interventions over purely clinical ones. By cultivating environments that support digital equity, health systems can improve resource allocation toward vulnerable populations, thereby promoting more inclusive public health outcomes. The global perspective is particularly instructive here, as comparative studies in LMICs demonstrate the necessity of aligning AI deployment strategies with the infrastructural realities of local health systems (O'Neil et al., 2021).

In light of these systemic barriers, scholars and practitioners have proposed a range of solutions aimed at fostering more equitable AI implementation. One recurring proposal is the need for multi-sectoral collaboration. Aschbrenner et al. (2022) emphasized that healthcare institutions, community-based organizations, and technology developers must work together to design culturally sensitive AI tools that resonate with the lived experiences of the populations they serve. This collaboration not only enhances the relevance of AI solutions but also builds trust among communities that may otherwise be skeptical of technological interventions. Incorporating community perspectives into the design and implementation of AI tools ensures that these technologies are not imposed upon populations but rather co-created to address context-specific needs.

Training and education also emerge as pivotal elements in overcoming systemic barriers. Aschbrenner et al. (2022) further highlighted that healthcare providers require targeted training to effectively integrate AI tools into their practice. Without adequate training, the introduction of AI risks overwhelming already burdened healthcare professionals and may result in underutilization of available technologies. Equipping healthcare workers with the necessary skills to interpret and act upon AI-driven insights ensures that technological innovations translate into tangible health equity outcomes. These efforts must be complemented by the active involvement of communities in shaping the design and implementation of AI interventions, thereby fostering shared ownership and accountability.

Frameworks such as the Health Equity Across the AI Lifecycle (HEAAL) provide structured approaches for guiding organizations in deploying AI responsibly. Kim et al. (2024) introduced this framework to ensure that considerations of equity permeate every stage of AI development, from data collection to implementation and evaluation. HEAAL emphasizes the identification of potential biases in datasets, the design of algorithms with fairness in mind, and the continuous assessment of distributive impacts on different population groups. By embedding equity considerations throughout the AI lifecycle, this framework offers a pathway to more inclusive and accountable practices. Similarly, Chisolm et al. (2023) called for comprehensive monitoring and evaluation mechanisms that continuously assess the distributive effects of AI interventions. Such mechanisms ensure that unintended consequences are identified and mitigated, thereby fostering a culture of reflexivity and adaptability in AI deployment.

Despite these proposed solutions, the literature reveals enduring limitations that warrant critical reflection. A major limitation lies in the uneven representation of marginalized populations in health datasets. McNeill et al. (2023) observed that data inconsistencies and underrepresentation limit the generalizability of AI applications, often skewing findings toward majority populations. This reflects a structural issue in data governance that cannot be solved by technical adjustments alone. Similarly, Dang et al. (2023) noted that while SDOH significantly influence health outcomes, the integration of these determinants into AI models remains underdeveloped. This indicates a persistent gap in bridging the social and technical dimensions of health research. Addressing these limitations requires interdisciplinary collaboration that brings together expertise from social sciences, health informatics, and policy studies.

The definitional ambiguity surrounding health equity further complicates the landscape. Hoyer et al. (2022) emphasized that current conceptualizations often fail to capture the multidimensional and intersectional nature of health disparities. Without clear and consistent metrics for measuring equity, evaluating the effectiveness of AI-driven interventions becomes challenging. This limitation points to the need for research efforts that not only refine the technical aspects of AI but also develop comprehensive frameworks for assessing equity in health outcomes. By engaging with diverse disciplinary perspectives, future research can generate more nuanced and context-sensitive definitions of equity, thereby enhancing the relevance and applicability of AI solutions.

Finally, the literature underscores the importance of acknowledging the broader socio-political context in which AI operates. Brewer et al. (2020) cautioned that technological solutions cannot be divorced from the structural inequities embedded in healthcare systems. AI tools may provide novel insights, but their transformative potential is constrained if systemic inequities remain unaddressed. Recognizing this reality requires scholars and policymakers to move beyond viewing AI as a panacea and instead situate it within broader strategies aimed at dismantling the root causes of health disparities. Such strategies must be comprehensive, integrating policy reform, infrastructural development, digital inclusion, and cultural sensitivity to ensure that AI contributes meaningfully to the pursuit of health equity.

CONCLUSION

This narrative review highlights the transformative potential of Artificial Intelligence (AI) in addressing Social Determinants of Health (SDOH) and promoting health equity. The findings confirm that economic stability, housing, education, and digital equity are deeply interconnected and function as critical determinants shaping health outcomes. AI tools, particularly predictive models and advanced analytics, demonstrate substantial promise in mapping these relationships and enabling proactive interventions that can identify at-risk populations before health disparities deepen. However, significant systemic challenges persist, including algorithmic bias, fragmented and inconsistent data, infrastructural limitations, and the enduring digital divide. These barriers underscore the necessity of inclusive policy frameworks, equitable data governance, and multi-sectoral collaboration to ensure that AI technologies contribute positively to reducing inequities rather than exacerbating them.

The discussion further emphasizes the urgency of implementing policies that foster digital equity, expand technological infrastructure, and build capacity among healthcare providers. Proposed frameworks such as the Health Equity Across the AI Lifecycle (HEAAL) offer structured guidance for embedding equity considerations throughout AI design and deployment, while stakeholder participation remains vital in tailoring interventions to community-specific contexts. Future research should focus on expanding the scope of AI applications to encompass underexplored determinants such as education quality and community cohesion, alongside efforts to refine standardized definitions and measures of health equity. By prioritizing inclusive approaches and systemic reforms, AI can become a pivotal tool in creating sustainable, equitable health outcomes globally.

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