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Responsible & Ethical AI Utilization in Social Determinants of Health

Paige COLEMAN[1], Atif Farid MOHAMMAD[2]

[1]Healable Inc., Rockville, MD, USA, Paige.coleman@healable.com
[2]Capitol Technology University, Laurel, MD, USA, afmohammad@captechu.edu

Abstract: The impact of SDoH (Social Determinants of Health) on population health in general is a significant area of concentration. There are biased determinants and there are risk determinants, which are not always very prominent. The utilization of Responsible AI allows us to deal with the aforementioned for the decision makers to pinpoint the lacks/gaps in healthcare provision. It is vital to provide relevant resources to the people who might have the resources, however, the required ones are not given priority. By doing this provision, the service providers include the whole care continuum. This research is beneficial for CMS (Centers for Medicare & Medicaid Services), as well as for standard population health. Our research presented in this paper shows tangible results. We have found in the application of AI/ML in the vast arena of SDoH. The application of Healable AI provides the insightful decision making for the associated stakeholders with the healthcare spectrum.

Keywords: AI, Healable, Healthcare, ML, SDoH

Introduction

Social determinants of health have emerged as critical factors shaping population health outcomes, yet their complexity often obscures the most actionable intervention points for healthcare systems. Beyond the widely recognized determinants such as income and education, healthcare disparities arise from subtle biases and less prominent risk factors that traditional analytical approaches struggle to identify systematically. These hidden determinants create gaps in care delivery that disproportionately affect vulnerable populations, even when resources exist within the system but remain misallocated due to inadequate prioritization mechanisms.

The integration of responsible artificial intelligence into population health management offers a transformative approach to addressing these challenges by enabling stakeholders to identify and respond to healthcare provision gaps with unprecedented precision. Machine learning algorithms can analyze vast datasets to uncover patterns in social determinants that human analysis might overlook, while responsible AI frameworks ensure these insights do not perpetuate existing biases or create new forms of discrimination. This capability is particularly valuable for organizations like the Centers for Medicare and Medicaid Services, which must allocate resources across diverse populations while ensuring equitable access to care throughout the entire care continuum from prevention through treatment and follow-up.

This research demonstrates the tangible benefits of applying AI and machine learning methodologies to the complex landscape of social determinants of health. Through the implementation of explainable AI techniques, healthcare decision-makers gain actionable insights that connect resource availability with population needs, enabling more effective interventions that address both overt disparities and subtle gaps in service delivery. The findings presented in this paper illustrate how proposed algorithm application can transform population health management from reactive problem-solving to proactive, data-driven resource allocation that serves both standard populations and those facing systematic barriers to care.

State of the Art

Social informatics is a subfield of medical informatics that enhances healthcare by bridging technology and social contexts to better integrate social and health information (Pantell et al., 2020). It transforms how we understand and respond to social data, leveraging techniques like artificial intelligence (AI) broadly defined as computational systems performing human-level cognitive functions (Mintz & Brodie, 2019). This includes natural language processing (NLP), a specialized area of AI that computationally analyzes human language, and machine learning (ML), which employs statistical methods to identify patterns and build predictive models from data (Harrison & Sidey-Gibbons, 2021). By effectively gathering and analyzing this information, social informatics aims to improve patient care and health outcomes (Dorr et al., 2019; Conway et al., 2019).

AI technologies can harness the advantages of SDoH information to recognize what patients require (Patra et al., 2021; Lybarger et al., 2023) and address healthcare system strain and medical condition intricacy (D'Elia et al., 2022; Balicer & Cohen-Stavi, 2020). A prevalent form of AI called machine learning works by identifying, forecasting, and classifying results through pattern recognition in datasets linked to verified observations or established ground truth instances (Bearse, Mohammad, & Haque, 2021). While still at an early research phase, machine learning combined with natural language processing has shown promise in extracting various SDoH elements from electronic medical record information, including early life experiences (Singh, Mohammad, & Ur Rahim, 2025), social networks, housing circumstances, work status, and forecasting health results using SDoH factors.

Proposition

As cost and quality continue to shape the national conversation around healthcare, I believe we often overlook one of the most important factors in how people actually experience care the human mind. Behind every data point is a person trying to navigate complex emotions, environments, and responsibilities, and that navigation is directly tied to their sense of safety and stability. When we think about Maslow's Hierarchy of Needs, it becomes clear that no one can move toward healing, self-care, or growth if their most basic needs are unmet. If a person does not feel safe, secure, fed, or rested, expecting them to focus on health management or long-term behavior change is simply unrealistic. These are not just abstract theories; they represent the real-world barriers that keep individuals from engaging with the healthcare system in a meaningful way.

This is where I see artificial intelligence and machine learning playing a transformative role, not as replacements for human care, but as tools to *enhance* it. If we use AI responsibly, it can help identify patterns and gaps that humans alone might not see. By analyzing data tied to social determinants of health, AI can help uncover the underlying reasons why someone struggles to follow through with treatment, miss appointments, or manage chronic conditions. It can surface early warning signs that point to issues like food insecurity, housing instability, or emotional distress all before those challenges escalate into medical crises. But for this to be ethical and effective, we must design these systems with empathy at their core, ensuring that technology amplifies human understanding instead of replacing it.

We have always believed that healthcare's biggest challenge isn't what happens *in the office*, but what happens between visits. A 15-minute conversation with a doctor can be powerful, but it can't compete with the realities patients face every day when they go home. Responsible AI integration could help bridge this gap by extending support beyond those episodic moments connecting people to resources, community programs, or care coordinators who understand their personal circumstances. By embedding social and environmental awareness into the care process, we can make the system feel more human again one that listens, anticipates, and adapts to people's real lives rather than expecting them to fit into rigid healthcare structures.

If we bring these two ideas together, human psychology and responsible AI, we can finally begin to close the gap between patient behavior, cost, and quality. Healthcare should not be something that happens *to* people; it should evolve *with* them. When technology is guided by compassion and understanding, it can help individuals regain control over their health and rebuild confidence in the system meant to support them. The goal is not perfection but alignment creating a space where patients can move from surviving to thriving, from being managed to being empowered. That is where we believe the future of healthcare must go: one that honors both data and humanity equally.

Algorithm

The given algorithm depicts the Mathematical Formulation of SDOH Algorithm for Population P_{55+}.
Notation:

- P_{55+}: Population aged 55 and older
- $i \in P_{55+}$: Individual in the target population
- SDOH = $\{d_1, d_2, ..., d_n\}$: Set of n SDOH domains
- where d_1 = income, d_2 = housing, d_3 = food security, d_4 = social isolation, d_5 = transportation, d_6 = access to care

Step 1: Identification and Assessment

1.1 Screening Function:

$S: P_{55+} \rightarrow \{0,1\}^n$

$S(i) = (s_1(i), s_2(i), ..., s_n(i))$

where $s_j(i) = 1$ if individual i screens positive for domain d_j, 0 otherwise

1.2 Assessment Severity: For individuals with positive screening:

$A: \{i \in P_{55+} \mid \exists j: s_j(i) = 1\} \rightarrow \mathbb{R}^n$

$A(i) = (a_1(i), a_2(i), ..., a_n(i))$

where $a_j(i) \in [0, 1]$ represents severity level for domain d_j

1.3 Data Collection:

$D = \{(i, S(i), A(i), C(i)) \mid i \in P_{55+}\}$

where C(i) represents community-level context data for individual i

Subject to constraints:

- Privacy(D) $\geq \theta_{\text{priva}}$cy (privacy threshold)
- Ethics(D) = TRUE

Step 2: Understanding Interplay

2.1 Correlation Analysis:

$\rho_{jk} = \mathrm{Corr}(d_j, h_k)$

where h_k represents health outcome k, and ρ_{jk} measures correlation between SDOH domain j and health outcome k

2.2 Vulnerability Identification: Define vulnerable subgroups:

$V = \{V_1, V_2, ..., V_m\} \subseteq P_{55+}$

where $V_l = \{i \in P_{55+} \mid \text{vulnerability\_criterion\_l}(i) = \text{TRUE}\}$

Risk score for subgroup V_l and domain d_j:

$R(V_l, d_j) = (1/|V_l|)\ \Sigma_i \in V_l\ a_j(i)$

Step 3: Intervention and Resource Navigation

3.1 Intervention Mapping:

$$I: P_{55+} \times SDOH \rightarrow \mathcal{P}(Resources)$$

$$I(i, d_j) = \{r_k \in Resources \mid match(i, d_j, r_k) > \tau\}$$

where $\mathcal{P}$(Resources) is the power set of available resources and τ is a matching threshold

3.2 Intervention Components: Define intervention vector for individual i:

$$\Theta(i) = [\theta_1(i), \theta_2(i), \theta_3(i), \theta_4(i)]^T$$

where:

- $\theta_1(i)$ = resource_connection_score(i)
- $\theta_2(i)$ = community_program_participation(i)
- $\theta_3(i)$ = advocacy_benefit_index(i)
- $\theta_4(i)$ = care_coordination_level(i)

3.3 Optimization: Maximize overall impact:

$$\max \Sigma_{i \in P_{55+}} \Sigma_{j=1}^{n} w_j \cdot [a_j(i) - a_j'(i)]$$

subject to:

- Budget constraint: $\Sigma_{i \in P_{55+}} cost(\Theta(i)) \leq B$
- Resource constraints: $utilization(r_k) \leq capacity(r_k)\ \forall r_k \in Resources$

where $a_j'(i)$ is post-intervention severity and w_j are domain weights

Step 4: Monitoring and Evaluation

4.1 Impact Tracking: Define impact function at time t:

$$H(i,t) = f(SDOH(i,t), \Theta(i,t))$$

where H represents health outcomes

4.2 Longitudinal Assessment:

$$\Delta H(i) = H(i, t_1) - H(i, t_0)$$

$$\Delta SDOH(i) = ||A(i, t_1) - A(i, t_0)||$$

4.3 Feedback Integration:

$$F: P_{55+} \times \mathbb{R} \rightarrow [-1, 1]$$

$$F(i,t) = feedback\_score(i,t)$$

4.4 Adaptive Updating:

$$\Theta(i, t+1) = \Theta(i,t) + \alpha \cdot \nabla E(i,t)$$

where E(i,t) is effectiveness metric and α is learning rate

Step 5: Collaboration and Partnerships

5.1 Stakeholder Network:

$$G = (N, E)$$

where:

- N = {healthcare, social_services, government, community_orgs, ...}
- $E = \{(n_i, n_j, w_{ij}) \mid n_i, n_j \in N, w_{ij} = collaboration\_strength\}$

5.2 Coordination Efficiency:

$$CE = (\Sigma_{(i,j) \in E}\ w_{ij} \cdot success(i,j)) / |E|$$

5.3 Community Engagement Index:

$$CEI = (|\{i \in P_{55+} \mid engaged(i) = TRUE\}|) / |P_{55+}|$$

Target: $CEI \geq \beta$ (minimum engagement threshold)

Overall Algorithm Objective:

Maximize: $\Psi = \Sigma_{i \in P_{55+}} [w_1 \cdot \Delta H(i) + w_2 \cdot \Delta SDOH(i) + w_3 \cdot F(i) + w_4 \cdot CEI]$

Subject to:
- $S(i)$ performed $\forall i \in P_{55+}$
- $A(i)$ performed $\forall i$ where $\Sigma_j s_j(i) > 0$
- Privacy and ethical constraints satisfied
- Budget $\leq B$
- $CE \geq \gamma$ (minimum coordination threshold)

where w_1, w_2, w_3, w_4 are weights reflecting relative importance of health outcomes, SDOH improvement, satisfaction, and engagement.

Conclusion

The implementation of this mathematically formalized SDOH algorithm offers healthcare organizations a systematic, data-driven framework to address the multifaceted social needs of their aging patient population, ultimately leading to measurable improvements in both clinical outcomes and operational efficiency. By integrating routine screening, individualized assessment, and tailored interventions with continuous monitoring and multi-sectoral collaboration, healthcare systems can proactively identify and mitigate social barriers that contribute to poor health outcomes, preventable hospitalizations, and increased healthcare costs among individuals aged 55 and older. The algorithm's optimization function ensures resource allocation is maximized within budgetary constraints while maintaining high levels of patient engagement and care coordination, thereby reducing health disparities, enhancing patient satisfaction, and improving population health metrics. Furthermore, the adaptive nature of the framework allows healthcare organizations to continuously refine their interventions based on real-time feedback and outcome data, creating a sustainable, person-centered approach that not only addresses immediate social determinants but also builds long-term community partnerships and institutional capacity for holistic care delivery. This comprehensive strategy positions healthcare organizations to meet value-based care objectives, reduce total cost of care, and fulfill their commitment to health equity in an increasingly complex healthcare landscape.

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