The Potential for Health Information Technology Tools to Reduce Racial Disparities in Maternal Morbidity and Mortality

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Abstract

Health information technology (health IT) potentially is a promising vital lever to address racial and ethnic, socioeconomic, and geographic disparities in maternal morbidity and mortality (MMM). This is especially relevant given that approximately 60% of maternal deaths are considered preventable.[1–36] Interventions that leverage health IT tools to target the underlying drivers of disparities at the patient, clinician, and health care system levels potentially could reduce disparities in quality of care throughout the continuum (antepartum, intrapartum, and postpartum) of maternity care. This article presents an overview of the research (and gaps) on the potential of health IT tools to document SDoH and community-level geocoded data in EHR-based CDS systems, minimize implicit bias, and improve adherence to clinical guidelines and coordinated care to inform multilevel (patient, clinician, system) interventions throughout the continuum of maternity care for health disparity populations impacted by MMM. Telemedicine models for improving access in rural areas and new technologies for risk assessment and disease management (*e.g.*, regarding preeclampsia) also are discussed.

Keywords: health information technology, maternal care, disparities

Introduction

HEALTH INFORMATION TECHNOLOGY (health IT) potentially is a promising vital lever to address racial and ethnic, socioeconomic, and geographic disparities in maternal morbidity and mortality (MMM). This is especially relevant given that ~60% of maternal deaths are considered preventable.[1–3] Although research is in progress, the limited published studies indicate that health IT tools—such as electronic health records (EHRs), patient portals, clinical decision support (CDS) systems, telemedicine models, and new technologies (*e.g.*, automated algorithms)—may yield health benefits for populations that experience health disparities—such as racial and ethnic minorities, the socioeconomically disadvantaged, and underserved rural populations—by enhancing patient engagement, improving implementation of clinical guidelines, promoting patient safety, and reducing adverse outcomes.[4–6]

Interventions that leverage health IT tools to target the underlying drivers of disparities at the patient, clinician, and health care system levels potentially could reduce disparities in quality of care throughout the continuum (antepartum, intrapartum, and postpartum) of maternity care. Research indicates that a sizeable portion of racial and ethnic disparities in

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severe maternal morbidity (SMM) and mortality can be attributed to variations in hospital quality.[3,7,8] Howell contends that a multipronged approach to quality improvement (QI) is needed throughout the care continuum to reduce racial and ethnic disparities in MMM.[9] This multipronged method emphasizes the significance of social determinants of health (SDoH) and incorporates patient factors (e.g., socioeconomic status, race/ethnicity, biology, genetics, and beliefs), community and neighborhood factors (e.g., social networks, built environment, and housing), clinician factors (e.g., knowledge, implicit bias, and communication), and system factors (e.g., access to high-quality care, structural racism, social and political policies, and health care institutions).

This article presents an overview of the research (and gaps) on the potential of health IT tools to document SDoH and community-level geocoded data in EHR-based CDS systems, minimize implicit bias, and improve adherence to clinical guidelines and coordinated care to inform multilevel (patient, clinician, and system) interventions throughout the continuum of maternity care for health disparity populations impacted by MMM. Telemedicine models for improving access in rural areas and new technologies for risk assessment and disease management (e.g., regarding preeclampsia) also are discussed.

SDoH and MMM

SDoH—the environmental context and social conditions in which people live, work, and play—are important factors to consider when examining causes of maternal mortality in the United States and approaches to address them. A 2018 study examining population-level factors and the rising maternal mortality between 1997 and 2012 found that an increased prevalence of chronic health problems, such as obesity and diabetes, only partially explained the worsening maternal outcomes in the United States.[10] Study findings showed that the increase in maternal mortality also was attributable to the proportion of women of childbearing age who did not complete high school, the proportion of births among African American women, and the proportion of women who attended fewer than 10 prenatal visits.[10] A 2018 commentary in the Journal of the American Medical Association emphasized addressing social inequality as key to reducing high maternal mortality rates in the United States.[11] It cited research on specific SDoH, including the link between adverse childhood events and chronic health problems, the cumulative stress of poverty and long-term outcomes, and how racism can lead to ''weathering'' or accelerated aging, which is related to increased rates of chronic health problems and, potentially, maternal mortality. A literature review in 2020 examining the relationship between SDoH and pregnancy-related mortality and morbidity found strong evidence for the effects of race and ethnicity, health insurance, and education on maternal mortality and severe morbidity.[12] The review indicated a need to evaluate a wider array of determinants—such as the role of socioeconomic and political context or area-level physical and material circumstances impacting maternal outcomes, the mechanisms that underlie observed associations of determinants, and the use of more diverse study designs. Thus, expanding research in this area may help in developing interventions to reduce inequities in MMM rates in the United States.

In addition, a report on the integration of social and medical care suggests that consideration of SDoH in clinical decision-making and addressing upstream factors is important to the current shift in the health care sector toward value-based payments and the focus on prevention and health promotion, rather than simply service delivery.[3] The report indicates that health IT innovations potentially could address health-related social needs and recommend responses to social risks (adverse social determinants) involving patient-centered care models that routinely include social risk data in care decisions. However, the authors note that although federal funds stimulated the digitization of health care via the adoption of EHRs, social care has not benefited from the same resources and policy attention and, thus, lags in digitization. Despite this gap, EHRs are a promising venue for storing SDoH collected from patients, and inclusion of these data in EHRs/CDS systems could be important for advancing population health equity.[4,13]

EHRs not only provide clinicians with important data for holistic patient assessment and aid in clinical decision-making, but they also provide a source of population health data. Professional organizations such as the National Academy of Medicine endorsed the standardization of SDoH screening in EHRs.[14] However, key challenges exist before the data match medical data in terms of being readily accessible and actionable.[15] Challenges include a lack of consensus on standards for capturing SDoH in EHRs and evidence that, once data are collected, referrals to community services will address social determinants effectively.[15] Research is lacking about optimal models for including and using SDoH in EHRs/CDS systems to advance health equity for racial and ethnic populations.[4,16]

Despite the research gaps, one could argue that integrating data on SDoH into EHRs/CDS systems may result in improving the quality of care for women of childbearing age and better risk monitoring throughout the continuum of maternity care. For example, these data could be used to adjust individual disease risk.[17] Fiscella et al. considered poverty to be an independent risk factor and integrated patient income data into heart disease risk score calculations in the 10-year Framingham study.[18] This proved to be a better way of identifying at-risk patients for heart disease than traditional calculators. In the same manner, such factors as race, poverty, and education could be used to identify women who are at higher risk of maternal complications, which may lead to improved risk monitoring throughout pregnancy and postpartum to ensure the quality and safety of maternity care for all women.

In addition, advances in big data, geospatial technology, and public access to large data sets that provide contextual information also make it possible to embed community-level geocoded data into EHRs as an alternative to, or complementary to, patient-derived data. CDS tools potentially could provide alerts to health care teams for patients who would benefit from targeted preventive or therapeutic interventions based on a community-level predictor (e.g., high unemployment) or public health concern.[4] In 2014, the U.S. President's Council of Advisors on Science and Technology (PCAST) issued a report that produced a comprehensive set of actions and goals to improve health care across the nation, using systems-engineering principles. A member of the PCAST council, Deryk Van Brunt, developed recommendations for the national implementation of community health

records (CHRs) to accomplish some of these goals.[19] He defined CHRs as ''a curated set of population-level indicators that describe the health and quality of life of a geographic community'' and pointed out that when place-based CHR data are linked to EHRs, an index of community-level SDoH or a ''vulnerability index'' can be calculated and may assist in medical interventions.[19] Evidence supports the idea that place-based social determinants represent identifiable risks for maternal mortality.[10] Moreover, CHRs usually are aggregated at the neighborhood level and include clinical, SDoH, and public health data. Thus, incorporating place-based CHR data into EHRs/CDS systems may help inform medical and population-directed public health interventions and health policies to address disparities in MMM.

Quality of Care and MMM

Intrapartum care represents an important period in the maternity care continuum that involves interactions among the patient, clinician, and other health care team members and often is when racial and ethnic disparities in maternal outcomes are revealed. Specifically, site of care, implicit bias, poor communication skills, and lack of cultural competence have been found to contribute to adverse maternal outcomes.[3,8,9] A 2018 report from the Agency for Healthcare Research and Quality revealed that in-hospital mortality for black mothers was nearly three times that of white mothers (10.0 vs. 3.7 per 10,000 delivery hospitalizations).[20] The analysis further indicated that compared with deliveries that did not involve SMM, those that did were more likely to occur at hospitals that have a mission to serve vulnerable populations, including minority-serving (53.4% vs. 44.3%). Research by Howell et al. revealed that hospitals with a disproportionate number of black deliveries had higher risk-adjusted SMM rates for both black and white women who delivered in these hospitals.[8,9] Using a simulation model, Howell[9] also found that if black women gave birth at the same hospitals as white women, the SMM rate of black women would decrease by 47.7%, from 4.2% to 2.9% (1.3 events per 100 deliveries per year). Implicit bias—defined as the reactive behaviors to such patient characteristics as age, race, ethnicity, gender, sexual orientation, physicality, and disability—also impacts the patient-clinician relationship.[21] These biases are activated unconsciously and can influence clinical decision-making that leads to differential treatment of patients.[3,21,22] Patients also can bring their own implicit biases to the clinical encounter.[21] Although provider concordance may help, research evidence about the impact of racial concordance on pregnancy care is sparse, given the low numbers of obstetricians and midwives of color.[3]

Overall, these factors—including inappropriate or delayed diagnosis or treatment and lack of adherence to clinical guidelines—account for a majority of preventable MMM events that could be addressed by QI initiatives.[3,9] QI initiatives recommend actionable steps focused on standardizing care delivery to reduce inequities and improve care at all hospitals—especially low-performing hospitals that serve a disproportionate number of racial and ethnic minority women.[3,9,23] Health IT tools potentially can be beneficial in these efforts. In fact, the recent report on birth settings in America recommended that the use of health IT to engage, inform, and support childbearing women be included in the

additional performance measures currently under consideration to address gaps in the maternal and newborn performance measures endorsed by the National Quality Forum.[3] These measures are relevant for creating a performance measurement and improvement infrastructure for maternity and newborn care, including mechanisms for public reporting, accountability, QI, and funding, as well as allowing childbearing women to make informed choices among health plans, maternity care providers, and birth settings.[3]

Examples of QI initiatives include the AIM care bundles developed by the Council on Patient Safety in Women's Health Care's Alliance for Innovation in Maternal Health (AIM) Program, and the Obstetric Data Definitions project by the American College of Obstetricians and Gynecologists (ACOG). The AIM initiative develops and implements maternal safety bundles (*e.g.*, reduction of peripartum racial/ethnic disparities) of evidence-based care approaches to prepare for, identify, prevent, and respond to the leading causes of maternal mortality and severe morbidity. In addition, ACOG's efforts to precisely define essential terms related to the mode of birth, hypertension, labor, rupture of membranes, gestational age, and parity are intended to ensure incorporation of these definitions into clinical practice and serve as standards for EHRs, coding, clinical practice guidelines, and policy statements.[3,24,25]

In addition to educating clinical care teams about racial/ethnic disparities in MMM, AIM care bundles and other recommendations emphasize shared decision-making as a strategy for improving communication and enhancing quality of care to reduce disparities.[3,9,23–25] Decision aid tools have been found useful for promoting shared decision-making and for assisting patients' understanding of their risks and treatment options.[3,26] Research studies about high-quality, evidence-based online decision aids and culturally appropriate risk assessment tools that incorporate medical, obstetrical, and social factors that influence birth outcomes are needed to foster informed choice,[3] as well as an evaluation of their effect on racial disparities in MMM. Implementation of disparity dashboards and the move toward multidisciplinary reviews of MMM also may enable hospitals to monitor their performance with different racial and ethnic groups.[9,23]

QI initiatives also include such tools as protocols, checklists, triggers (*e.g.*, maternal early warning criteria), evidence-based practices, and simulation training[9,23,27]—all of which could be incorporated into EHRs/CDS systems to facilitate standardization of care and reduce disparities in quality of care for racial/ethnic minority women. Although more studies are needed, the few existing studies do indicate that health IT investment can reduce disparities in care processes and standardization.[4,28–30] Thus, better clinical care coordination via health IT potentially could improve clinician performance and adherence to clinical guidelines, reduce redundant testing resulting from clinician biases, detect treatment risks, and, consequently, promote equity in best practice care for all patients.[4,6,30]

Telemedicine and MMM

Inequities in health care access also contribute to racial disparities in MMM. Insurance coverage, socioeconomic status, availability of community resources, and site of care often limit racial/ethnic minority women's access to quality care.[3,8,9,20] Addressing rural and urban maternity care deserts

is an especially challenging part of the efforts to improve maternal outcomes. As a result of geographic disparities, women living in rural communities and underserved urban areas are at greater risk for preterm birth and maternal and infant mortality.[3] In addition, these challenges are more pronounced for racial/ethnic minority women living in rural areas, given the higher likelihood of occurrence of hospital closures and loss of hospital obstetric services in rural communities composed of a higher percentage of black, Hispanic, and unemployed residents.[31,32]

Telemedicine (also referred to as telehealth)—defined as the use of medical information that is exchanged from one site to another through electronic communication to improve a patient's health—is a promising solution.[33,34] The report on birth settings in America notes that telemedicine could be an appropriate component of demonstration model birth centers and hospital services in underserved rural and urban areas that could be created by the Health Resources and Services Administration to make quality maternity care more accessible.[3] In addition, findings from a review of obstetric telemonitoring indicated that this approach has much potential to contribute to improved gestational outcomes, early detection of complications, and the provision of local interventions before hospitalization.[35]

Examples of telemedicine programs that aim to increase health care access and address shortages in the maternity care workforce can be found across the United States. The Massachusetts Child Psychiatry Access Program for Moms (also known as MCPAPs for Moms) helps to combat mental health and substance use issues in pregnant and postpartum women by building the capacity of local obstetricians, primary care physicians, and pediatricians.[36] In Georgia, nurses are equipped with telemedicine carts to facilitate videoconferences between expectant moms and specialty providers.[37] In Wyoming, the successful use of phone applications increased the utilization of perinatal services.[38]

The use of telemedicine is an increasing area of interest for patients, clinicians, insurers, and legislators.[39–42] In March 2020, The Coronavirus Aid, Relief, and Economic Security (CARES) Act and Coronavirus Preparedness and Response Supplemental Appropriations Act loosened many telemedicine patient/service eligibility and reimbursement restrictions during the COVID-19 pandemic. State restrictions on telemedicine services, such as scope of practice or licensure requirements, remain in effect and continue to be monitored.[43] Research is needed to examine the impact and quality of telemedicine on maternal care and the unintended consequences on clinicians and patients.

Machine Learning and MMM

Machine learning (ML), the broad term referring to a collection of tools that provide predictions in a wide range of settings, is a method for diagnosing diseases or predicting clinical outcomes that has much relevance for maternal health.[44–46] Specifically, timely identification and care management of SMM is critical for preventing maternal death.[3,9] Likewise, predictive risk of complications at discharge has potential value for guiding postpartum care.[44]

Research findings from a pilot study of an ML framework to identify SMM using EHR data from more than 45,000 deliveries at a large academic medical center revealed that the team's predictive algorithm outperformed the Centers for Disease Control and Prevention's model.[47] The researchers identified a greater number of SMM cases with a smaller false positive rate than what is achieved through current practice and revealed novel indicators associated with SMM. The team noted that the lack of consensus on the various definitions of SMM presented a challenge to this work effort and indicated that their future plans will move beyond the use of a simple ML algorithm logistic regression to include more advanced tools (*e.g.*, neural networks, decision trees, support vector machines) to improve SMM identification performance. In another study using advanced ML tools, researchers demonstrated that in comparison to conventional statistical methods, ML algorithms improved the prediction performance of late-onset preeclampsia development using EHR data from early second trimester to 34 weeks in a sample of 11,000 women who received antenatal care.[45] The authors contend that although future studies are needed to prospectively verify the algorithms, their application to routine antenatal care could improve maternal outcomes. In a similar study, researchers successfully developed predictive models to identify maternal risk of postpartum hypertensive disorders and surgical wound infections that required hospital admission after delivery.[48]

Although ML tools are promising, research is needed to evaluate the impact of using automated algorithms to inform disease risk assessment, detection, diagnoses, and treatment decision-making on disparities in health care quality or outcomes. Research that informs best clinical practices for using predictive modeling are needed.[44] In addition, it is critical that software engineers and data scientists consider the voices of diverse women and ethicists in collaborative activities about these new technologies to mitigate unintended consequences and prevent the exacerbation of disparities.[49,50]

Conclusion

Health IT tools represent an opportunity to reduce inequities in quality and access in the U.S. maternity care system. Research is needed on multilevel interventions that leverage health IT tools to address disparities throughout the continuum of maternity care to ensure that all women can benefit from an evidence-informed U.S. maternity care system.

Disclaimer

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