

Redesign of Health Care Systems to Reduce Diagnostic Errors: Leveraging Human Experience and Artificial Intelligence

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Diagnostic errors are defined by the National Academies of Sciences, Engineering, and Medicine (NASEM) as the failure to either establish an accurate and timely explanation of the patient's health problem(s) or communicate that explanation to the patient.¹ According to a report by the Institute of Medicine, diagnostic errors account for a substantial number of adverse events in health care, affecting an estimated 12 million Americans each year.¹ Diagnostic errors are a common and serious issue in health care systems, with studies estimating that 5% to 15% of all diagnoses are incorrect.¹ Such errors can result in unnecessary treatments, delays in necessary treatments, and harm to patients. The high prevalence of diagnostic errors in primary care has been identified as a global issue.² While many factors contribute to diagnostic errors, the complex nature of health care systems, the limited processing capacity of human cognition, and deficiencies in interpersonal patient-clinician communication are primary contributors.^{3,4}

Discussions around the redesign of health care systems to reduce diagnostic errors have been at the forefront of medical research for years.^{2,4} To decrease diagnostic errors in health care, a comprehensive strategy is necessary. This strategy should focus on utilizing both human experience (HX) in health care and artificial intelligence (AI) technologies to transform health care systems into proactive, patient-centered, and safer systems, specifically concerning diagnostic errors.¹

Human Experience and Diagnostic Errors

The role of HX in health care cannot be overstated. The HX in health care integrates the sum of all interactions, every encounter among patients, families and care partners, and the health care workforce.⁵ Patients and their families have a unique perspective on their health care

experiences that can provide valuable insight into potential diagnostic errors.⁶ The new definition of diagnostic errors introduced in the 2015 NASEM report emphasized the significance of effective communication during the diagnostic procedure.¹ Engaging patients and their families in the diagnostic process can improve communication, improve diagnostic accuracy, and help to identify errors before they cause harm.⁷ However, many patients and families feel that they are not listened to or taken seriously by health care providers, and may not feel comfortable sharing information that they feel is important.⁸ To address this, health care systems can implement programs that encourage patients and families to be more engaged in the diagnostic process, such as shared decision-making, patient portals, and patient and family advisory councils.⁹ Health care systems must prioritize patient-centered care, teamwork, and communication. Patients and their families must be actively engaged in their care, and health care providers must be willing to work collaboratively and listen to patients' concerns.^{6,10}

Health care providers also bring their own valuable experiences and expertise to the diagnostic process, as they are often the ones on the front lines of patient care. However, health care providers may not always feel comfortable reporting errors or near misses, and may

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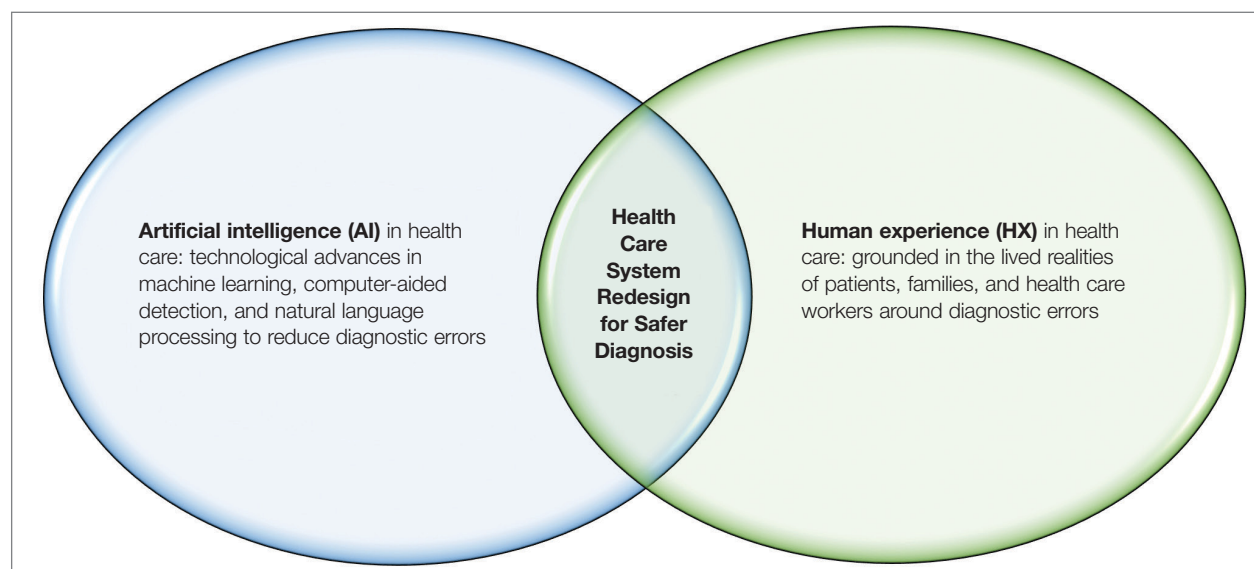


Figure. Leveraging human experience and artificial intelligence to redesign the health care system for safer diagnosis.

not have the time or resources to participate in quality improvement initiatives. To address this, health care systems can implement programs that encourage providers to report errors and near misses, such as anonymous reporting systems, just-culture initiatives, and peer review.¹¹ Creating a culture of teamwork and collaboration among health care providers can improve the accuracy of diagnoses and reduce the risk of errors.¹²

A key factor in utilizing HX to reduce diagnostic errors is effective communication. Communication breakdowns among health care providers, patients, and their families are a common contributing factor resulting in diagnostic errors.² Strategies to improve communication include using clear and concise language, involving patients and their families in the decision-making process, and utilizing electronic health records (EHRs) to ensure that all health care providers have access to relevant, accurate, and up-to-date patient information.^{4,13,14}

Another important aspect of utilizing HX in health care to reduce diagnostic errors is the need to recognize and address cognitive biases that may influence diagnostic decisions.³ Cognitive biases are common in health care and can lead to errors in diagnosis. For example, confirmation bias, which is the tendency to look for information that confirms preexisting beliefs, can lead providers to overlook important diagnostic information.¹⁵ Biases such

as anchoring bias, premature closure, and confirmation bias can lead to incorrect diagnoses and can be difficult to recognize and overcome. Addressing cognitive biases requires a commitment to self-reflection and self-awareness among health care providers as well as structured training of health care providers to improve their diagnostic reasoning skills and reduce the risk of cognitive errors.¹⁵ By implementing these strategies around HX in health care, health care systems can become more patient-centered and reduce the likelihood of diagnostic errors (**Figure**).

Artificial Intelligence and Diagnostic Errors

Artificial intelligence has the potential to significantly reduce diagnostic errors in health care (Figure), and its role in health care is rapidly expanding. AI technologies such as machine learning (ML) and natural language processing (NLP) have the potential to significantly reduce diagnostic errors by augmenting human cognition and improving access to relevant patient data.^{1,16} Machine learning algorithms can analyze large amounts of patient data sets to identify patterns and risk factors and predict patient outcomes, which can aid health care providers in making accurate diagnoses.¹⁷ Artificial intelligence can also help to address some of the communication breakdowns that contribute to diagnostic errors.¹⁸ Natural

language processing can improve the accuracy of EHR documentation and reduce the associated clinician burden, making it easier for providers to access relevant patient information and communicate more effectively with each other.¹⁸

In health care, AI can be used to analyze medical images, laboratory results, genomic data, and EHRs to identify potential diagnoses and flag patients who may be at risk for diagnostic errors. One of the primary benefits of AI in health care is its ability to process large amounts of data quickly and accurately.¹⁹ This can be particularly valuable in diagnosing rare or complex conditions. Machine learning algorithms can analyze patient data to identify subtle patterns that may not be apparent to human providers.¹⁶ This can lead to earlier and more accurate diagnoses, which can reduce diagnostic errors and improve patient outcomes.¹⁷ One example of the application of AI in health care is the use of computer-aided detection (CAD) software to analyze medical images. This software can help radiologists detect abnormalities in medical images that may be missed by the human eye, such as early-stage breast cancer.²⁰ Another example is the use of NLP and ML to analyze unstructured data in EHRs, such as physician notes, to identify potential diagnoses and flag patients who may be at risk for diagnostic errors.²¹ A recent study showed that using NLP on EHRs for screening and detecting individuals at risk for psychosis can considerably enhance the prognostic accuracy of psychosis risk calculators.²² This can help identify patients who require assessment and specialized care, facilitating earlier detection and potentially improving patient outcomes. On the same note, ML-based severe sepsis prediction algorithms have been shown to reduce the average length of stay and in-hospital mortality rate.²³

However, there are also concerns about the use of AI in health care, including the potential for bias and the risk of overreliance on AI. Bias can occur when AI algorithms are trained on data that is not representative of the population being analyzed, leading to inaccurate or unfair results, hence, perpetuating and exacerbating existing biases in health care.²⁴ Over-reliance on AI can occur when health care providers rely too heavily on AI algorithms and fail to consider other important information, such as the lived

experience of patients, families, and health care providers. Addressing these concerns will require ongoing efforts to ensure that AI technologies are developed and implemented in an ethical and responsible manner.²⁵

Conclusion

Reducing diagnostic errors is a critical goal for health care systems, and requires a comprehensive approach that utilizes both HX and AI technologies. Engaging patients and their families in the diagnostic process, promoting teamwork and collaboration among health care providers, addressing cognitive biases, and harnessing the power of AI can all contribute to more accurate diagnoses and better patient outcomes. By integrating the lived experience of patients, families, and health care providers with AI technologies, health care systems can be redesigned to become more proactive, safer, and patient-centered in identifying potential health problems and reducing the risk of diagnostic errors, ensuring that patients receive the care they need and deserve.

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