Envisioning Data-driven AI Technology in Asthma Care

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Artificial intelligence (AI) -assisted tools, such as expert systems and clinical decision support systems, have long been used in clinical settings with data obtained through clinical devices. These tools help clinicians make informed decisions through algorithms, based on patient data. With the recent advancement of consumer health informatics solutions, such as mobile apps and wearable devices, massive data are generated and makes it possible to expand the scope of AI-assisted tools to the consumer field, benefiting both providers and patients. In this paper, we outline an ongoing empirical study in a very data-intensive health problem – asthma. We interviewed 20 asthma specialists, unpacked their work practice and data needs, and encouraged them to envision future technology in support of both patients' asthma management and their work as providers. We identified different features of the imagined technologies and the barriers and concerns that these tools might bring to different stakeholders in different contexts.

CCS CONCEPTS • Human-centered computing → Collaborative and social computing; • Applied computing → Health care information systems;

Additional Keywords and Phrases: AI; Healthcare; Future of Work; Human-AI Collaboration; Human-AI Interaction; Trust AI

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1 INTRODUCTION

Artificial intelligence (AI) has been increasingly used in healthcare across many health domains [5,12]. AI-assisted tools, such as expert systems and clinical decision support systems, have long been used in clinical settings with data obtained through clinical devices. These tools help clinicians in making informed decisions through algorithms based on patient data. Research communities mainly study the potential of AI in few diseases [7], with dominant focuses on cancer [11], neurology [19], and cardiology [6]. Few works have attempted to look into how AI is used for or could be used in a long-term caring trajectory in supporting chronic illnesses.

Chronic diseases are the leading causes of death and disability in the US and managing and preventing chronic conditions is a time-consuming, and challenging task. With the advancement in consumer health informatics solutions, such as mobile apps, sensors, and wearable devices, patient's health data can now be automatically collected, integrated, and shared for various chronic care management and treatment purposes. Massively available data generated by these solutions also make it possible to expand the scope of AI-assisted tools in healthcare and extend to the consumer field. With AI techniques, such as machine learning, data generated by the consumer health informatics solutions could be potentially used for chronic care, benefit both clinicians (e.g., to aid in clinical decision making and create personalized self-management plan for patients) and patients (e.g., predict worsen symptoms in long term care management).

Food (data) is now available for AI to assist patients and clinicians. However, data-driven AI solutions have not been widely used among consumers, nor for managing chronic conditions purposes. We are at the beginning stage of envisioning what these AI-assisted technologies can be and how can we design them to support patients with chronic conditions as well as their healthcare providers. It is crucial for Human-computer Interaction (HCI) researchers to study the stakeholders who will be using these tools to design them right to avoid unintended consequences[18].

In this paper, we outline an ongoing empirical interview study in a very data-intensive health problem – asthma. Asthma is one of the most common chronic diseases. In the US, one out of 13 people has asthma. There is no cure for asthma and that makes data crucial in the long-term management of asthma. To get a patient's asthma under good control, patients and healthcare providers need to analyze and make use of patient's health data collected in their everyday routines such as types, severity, and triggers of symptoms, and medication usage. Through interviewing healthcare professionals who consider as asthma specialists, we aim to unpack their work practices and data needs in asthma care as well as to encourage healthcare professionals to imagine future technology to support the long-term care of asthma patients and their work.

2 STUDY APPROACH

2.1 Envisioning Future Technology in Asthma Care with Healthcare Professionals

The imaging, crafting, and the making of future technology usually reflect the visions of privileged scholars, media as well as technology companies. Inspired by the feminist and post-colonial discourses, we questioned ourselves that "Who should be the designer of the future technologies in supporting asthma care?" We decided to democratize technological imagination and allow our participants to envision the future supporting technology grounded in their current work practice and personal truth.

2.2 Realizing AI in Healthcare and its (Perceived) Challenges and Concerns

As AI has gained wide attention in public and academia in recent years, there is an increasing interest in designing and adopting AI-assisted tools in healthcare. HCI researchers have studied how AI tools are impacting healthcare in different health domains, such as pathology[2], cardiology[17], and radiology[15]. Studies have explored the design, usage, and user experience of AI in healthcare. For instance, researchers have attempted to develop novel interaction modalities to better incorporate AI into clinicians' decision-making processes without infringing upon their autonomy, or to design more intelligent chatbots to improve perceived intimacy and enjoyment through the promotion of the reciprocal effect [8,17]. These studies collectively point to the importance of studying AI applications in healthcare beyond their technical robustness (e.g., predictive accuracy), to include additional dimensions such as user activation, sociotechnical integration, privacy, and health disparity [3,9,10].

In real-world healthcare settings, the HCI community identified several (perceived) challenges and concerns of adopting AI tools, such as explainability [13,16], and transparency [1]. Researchers also identified challenges beyond the technical aspects of AI. For example, Wang and Wang, et al. have studied AI-assisted clinical decision support tools and identified user experience issues of the system [14]. Carrie J. Cai, et al. studied the information needs of medical experts during their introduction to an AI assistant and pointed out future work should investigate how to efficiently design onboarding training materials to help end-users effectively use the AI tools [2]. These works studied how humans are interacting with AI, addressing the single user (e.g., clinicians), but not other contextual factors that may influence the use of such systems.

In this paper, we conducted interviews with asthma specialists to unpack their work practice and data needs and encourage them to imagine future supporting technologies that can both benefit patients' long-term asthma management and their work. We identified different features and goals of the imagined technologies as well as the barriers and concerns that these tools might bring to different stakeholders (e.g., patients and providers) in different contexts (e.g., hospital and healthcare system).

3 METHOD

We conducted an empirical interview study 1) to understand the current data practice that asthma specialists have adopted to treat patients, and 2) to envision future technologies in support of providers' data needs and practices in asthma care.

3.1 Recruitment

We recruited participants who are considered medical professionals in an urban neighborhood on the east coast of the United States. This neighborhood has one of the highest deaths and disease rates from asthma in the US and is considered as low socioeconomic (SES) with rampant health and economic disparities. To protect our participant's anonymity, we decided to not disclose the location and the name of the medical center and the hospitals.

In total, we recruited 20 participants through snowball sampling. All participants work in the same academic medical center, teaching hospital, and its adjacent children's hospital located in the neighborhood. Among 20 recruited participants, all are considered asthma specialists who have extensive experience working with either pediatric or adult asthma patients, and in many cases, both. In summary, our participants represent a variety of roles in asthma care in the clinical settings including out-patient, in-patient, and emergency care, ranging from pediatric emergency room physician (6), primary care physician (6), nurse practitioner (3), nurse (2), pharmacist (1), physician assistant (1), and allergist (1). Our participants include fellows, residents as well as attending physicians. Overall, participants have an average of 8 years of experience treating and caring for asthma patients, ranging from 0.5-35 years.

3.2 Data Collection

We conducted 20 interviews with 20 asthma specialists. Our interview consists of two parts. In the first part of the interview, we unpack medical professionals' work practice and data needs in asthma care. To do so, we asked questions around 1) how are patient-generated health data currently being shared with and used by medical professionals in asthma care? and 2) what types of patient-generated health data do medical professionals wish to have access to in order to facilitate their work to treat asthma? In the second part of the interview, we aim to democratize technological imagination and allow our participants to imagine and narrate a future technology by asking what a perfect technology would be like in support of the care of asthma patients as well as medical professionals. After participants finish narrating

their imagined future technology, we probe questions around their rationale of why they think such technologies would be useful, as well as their perceived challenges and concerns that these technologies may bring along.

We designed our interview into two parts for several reasons. The first part of the interview allows our participants to reflect on their current work, data, and technology practice. This prepares our participants for the second part of the interview by assisting them to root their imagined future technology in their own knowledge and experiences. It also helps our participants to ground the challenges and concerns of their imaginary future technologies to the current medical world. The first author conducted all interviews individually with one participant at a time to avoid the power dynamic between different roles in medicine, ensuring each participant can express freely without receiving any judgment from their peers.

We reached theoretical data saturation after conducting 18 interviews. We managed to balance different job roles after data saturation and decided to conduct two more interviews to ensure we collected sufficient data. Each interview lasted between 40 mins to 1.5 hours with an average being 1 hour. All interviews were conducted between November 2020 to January 2021. We received verbal consent from all participants to participate in this study. Each participant was compensated $50 for their time and efforts. Due to the Covid-19 pandemic, to protect the safety of authors, our participants, and the public, all interviews were conducted online through zoom. All interviews were audio-recorded with participant's consent. Our study is considered self-exempted according to the institutional review board (IRB).

3.3 Data Analysis

All interviews were audio-recorded and transcribed for data analysis. We inductively approached our data [4]. Two authors first read a subset of data individually and meet weekly to discuss codes and identify ways of coding the data. In this process, codes such as features of the future technologies (prediction, profiling patient, etc.), personal level concern (trust, burden, responsibilities, etc.), organizational level concerns (workflow, work process, etc.) emerged. Based on the initial analysis and discussion, the authors identified the intricate relationship between multiple stakeholders (clinicians, patients) with the imagined future technologies (patient-facing, provider-facing) in multiple contexts (hospital, healthcare system). The authors are currently finishing coding the rest of the data focusing on the innovations (characteristics of the imagined technology and challenges of realizing it) and how will they influence the recipients (providers and patients) in different contexts (local hospital, healthcare system).

4 CONTRIBUTIONS

We are currently conducting an in-depth analysis of our data. We found out that medical professionals imagined technologies are both patient-facing (e.g., a tracking tool to assist patients to track their symptoms and predict asthma attacks) and clinician-facing (e.g., using patient-generated health data to recommend providers with treatment plans or predict high-risk patients). Medical professionals wish the AI techniques can assist them with the "data work" (making sense and use the patient-generated health data) and make their work more efficient, but they fear that introducing new technology will bring more burden. They reveal that they need human partnership (e.g., checking with the patients themselves) to trust the system output (e.g., classifying a patient into high risk). At the hospital and healthcare system level, medical professionals concern about the future of work in medicine, questioning who should triage the "AI-prompted alerts" after new technologies being implemented and the potential of losing their clinical instincts to treat patients by overly relying on AI-generated recommendations. When it comes to patients, medical professionals worry about the advancement of technology could leave vulnerable patients behind from not have access to patient-facing technology (e.g., mobile app) or having low digital health literacy.

We only interviewed asthma specialists in this study, thus our work only covers asthma patient's needs and concerns from providers' perspectives. This study could further our understanding of healthcare professional's current work practices, data needs, and technology needs in asthma care. We also identified design opportunities for future data-driven AI systems in support of asthma patients as well as medical professionals. This finding could potentially be broadly applied to other chronic conditions such as obesity, hypertension, and diabetes.

We are excited to discuss the methods that we used to study human-centered AI in the real-world healthcare setting, as well as our findings, that are touching many relevant topics of the workshop's interests, including trust, human-centered explanation of AI, and challenges and concerns of adopting AI in real-world healthcare settings on both individual and organizational level. We hope to learn from other researchers' insights and experiences on conducting empirical work in understanding and designing human-AI interaction in real-world healthcare settings.

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