

**Raising the stakeholders: Improving patient outcomes through interprofessional collaborations in AI for healthcare**

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Research into AI implementations for healthcare continues to boom. However, successfully launching these implementations into healthcare clinics requires the co-operation and collaboration of multiple stakeholders in healthcare including healthcare professionals, administrators, insurers, legislators, advocacy groups, as well as the patients themselves. The co-operation and collaboration of these interprofessional groups is necessary not just in the final stages of launching AI based solutions in healthcare, but along each stage of the research design and analysis. In this workshop, we solicited talks from researchers who have embraced the idea of interprofessional collaboration across many different stakeholder groups at multiple stages of their research. We specifically focus on projects which included heavy collaborations from healthcare professionals, embraced the research subjects' communities as critical research partners, as well as included researchers who are advocating

for systemized changes to include interprofessional stakeholders as evaluators of AI research in healthcare.

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## 1. Introduction

Artificial intelligence (AI) and other computational and bioinformatic approaches have become a critical component of biomedical research. The wealth of available medical data and pertinent research questions have driven experts across many scientific fields to begin developing computational methods to drive innovation in medical research. However, AI in healthcare is often labelled as “disruptive,” a word simultaneously embracing its innovative nature, while warning against its turbulent impact on a broad range of health-care related disciplines. As a result, many healthcare stakeholders continue to be reserved, and even outright resistant, to AI advances for clinical outcomes.

Healthcare stakeholders include researchers across a variety of disciplines, clinicians, patients, insurers, legislators, lawyers, economists, UN agencies, government, private and non-profit organizations, to name a few. Reservations regarding AI healthcare research from any stakeholder group creates both hard barriers (restrictive legislation) and soft barriers (aversion to data sharing) in conducting, validating, and implementing AI approaches in the clinic. Ford et al., note “(r)esearchers who work in cultural silos are unlikely to maximize the potential of patient data”<sup>1</sup> and recommend meaningful stakeholder involvement is necessary at every stage of research in order to remove barriers for clinical translation.

However, there is no straightforward strategy for creating meaningful involvement mechanisms across many healthcare stakeholders. In this workshop, we aim to invite talks focusing on AI approaches in biomedical research from diverse and inclusive research teams, with expertise that spans different academic and professional disciplines, or who have collaborated with or studied the perspective of various stakeholders of computational healthcare research. Specifically, talks will emphasize both lessons learned from collaborative research and how the collaboration influenced the design, interpretation and overall positioning of the results, as well as provide advice for how other researchers can engage in their stakeholder community.

## 2. Effective medical research requires active involvement of medical professionals

Research into AI tools aimed at improving clinical outcomes needs to evaluate not only technical performance, but socio-technical performance outcomes. It is inevitable that the introduction of AI technologies to clinics will cause breaks and necessitate changes to existing systems.<sup>2</sup> Medical professionals are essential to include as active participants in AI biomedical research to design tools that minimize these breaks but also to act as diplomats and repairmen to bring AI to its full medical potential.<sup>2</sup> This socio-technical approach to AI research is exemplified by the ‘Sepsis Watch’ project led by Dr. Mark Sendak and other researchers at Duke University.<sup>3</sup> One of the critical factors influencing the potential of Sepsis Watch to improve septic patient outcomes was

the integration of the tool into existing social and professional dynamics – and active involvement from rapid response team nurses was essential for this to occur.<sup>2</sup> Following observations of Sepsis Watch during its first two years of implementation, these researchers posed four key values necessary for the translation of biocomputing research into medical practice: rigorously defining the problem, building relationships with key stakeholders, respecting professional discretion, and creating an ongoing feedback loop with stakeholders.<sup>3</sup>

### **3. Study subjects and their communities must also be treated as research partners**

Beyond the inclusion of medical professionals in AI research, study subjects themselves are critical collaborators whose experiences and communities influence the ability of AI driven tools to improve clinical outcomes. Dr. Lisa Vizer recently published a qualitative study which investigated the friction points of tracking health indicators of chronic disease. Vizer proposed a Conceptual Model of Shared Health Informatics (CoMSHI) that specifically identifies that tracking tools need to consider the social context of the person with chronic illness, including not only health professionals but also informal carers. They recommend that tools need to be reflective of the shared work of many community members in the tracking and monitoring of chronic illness and need to be designed to easily be used by multiple members in the participants' community as well as the participants themselves.<sup>4</sup>

The Wall Lab at Stanford University has embraced the idea of creating tools aimed at serving various stakeholders of the autism community. They have developed 'SuperpowerGlass,' a product based off Google Glass, as a wearable device for children with Autism Spectrum Disorder (ASD) which in real-time classifies the emotions of their family and peers while also recording interactions for additional insight. As well, they have launched a therapeutic mobile-device game called 'Guess What?' which tests children's abilities to act out and identify emotions while recording their play time as a long-term data source from which behavioral improvement can be measured. A critical aspect of both of these technologies is that insights and data are visible to parents and carers so they can also review and learn from their child's interactions. Moreover, the Wall lab has developed a crowd sourced ASD screening tool using home videos of children which alleviates the long wait times for official ASD diagnoses and allows critical early intervention for behavioral improvement. The Wall lab has also used machine learning algorithms to identify the most important questions used by clinicians in diagnosing ASD so that questionnaires and time-to-diagnosis can be shortened.<sup>5</sup>

Dr. Dan Gillis works as part of a team that is building computational infrastructure for the Inuit community in Rigolet, Nunatsiavut, Canada. A critical aspect of this research is working in partnership with the community to develop Inuit-led monitoring systems to understand and respond to not only classic metrics of climate change, but also to intangible losses that are priorities for the Inuit people. Involving the Inuit perspectives in the design, maintenance, and use of the monitoring system allows them to understand and mitigate the impacts of climate change in their community. Furthermore, they advocate for community-specific priorities in terms of public health and how climate change influences the health of the community considering the perspectives of researchers, public health officials, and the Inuit community itself.<sup>6</sup>

#### 4. Precision medicine has accelerated the need for systems that evaluate the promise of AI research from multiple stakeholder perspectives

AI has become a critical driver of biomarker discovery and precision medicine, but there are few systems in place to evaluate the efficacy and make appropriate recommendations for these discoveries.<sup>6</sup> Dr. John Carethers, in partnership with the National Academies of Sciences, Engineering, and Medicine, co-authored a report proposing a roadmap to address the lack of systems for evaluating precision medicine research. The team interviewed federal regulators, insurers, developers of biomarker tests, medical professionals, and advocacy groups to identify 10 goals for establishing systems for the evaluation of precision medicine research including standardizing patient and provider information, studying different demographic groups, developing evidence-based guidelines for clinical practice, and maintaining a robust database to share findings.<sup>7</sup>

Dr. Amar Das has proposed an interdisciplinary, phased research framework to better evaluate AI tools and applications in healthcare, similar to the multi-phase system used to approve novel drugs. They propose the following phases: discovery and invention, technical performance and safety, efficacy and side effects, therapeutic efficacy, and safety and effectiveness. Critically, at all stages of their research framework user feedback and continuous monitoring is essential in evaluating and updating AI implementations for clinical practice.<sup>8</sup>

#### 5. Conclusion

Given the current state of biocomputing, it is inevitable that AI will be a critical driver of biomedical innovation. However, it is of utmost importance that researchers engage with and secure the trust of healthcare stakeholders to maximize the potential of AI in improving patient outcomes. As Obermeyer & Lee stated, “machine learning in medicine will be a team sport, like medicine itself. But the team will need some new players [...] who can contribute meaningfully to algorithm development and evaluation.”<sup>10</sup> It is our hope that this workshop will galvanize computational researchers to engage with stakeholders in meaningful ways and move AI from being “disruptive” to “progressive.”

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